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Essays on Worker Promotion and Wage Growth

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Graduate Program in Economics
A thesis submitted in partial fulfillment of the requirements for the degree in Doctor of Philosophy

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by

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Abstract

This thesis consists of three chapters in the field of labor economics related to worker promotion, hierarchical levels, and wage growth.

Chapter two examines the impact of the skill requirements of an occupation on the likelihood that a worker receives a promotion. Promotion data are taken from the National Longitudinal Survey of Youth 1979, while skill requirements data come from the Dictionary of Occupational Titles. I find that the higher the cognitive skill requirement of an occupation, and the lower the motor and strength skill requirements, the higher the probability that the worker receives a promotion. Introducing skill requirements reduces the effect of the worker's Armed Forces Qualification Test score on promotion, while it increases the gender gap in promotion.

Chapter three assesses the importance of hierarchical levels to skill accumulation and career outcomes by estimating an occupational choice model. Using labor market history data from the German Socio-Economic Panel, and task usage data from the German Qualification and Career Survey, I demonstrate that hierarchical level significantly impacts labor market outcomes and task usage within the occupation. To capture these features of the data, I build an occupational choice model with levels where workers accumulate both task-specific and occupation-specific human capital through learning-by-doing. I use indirect inference to estimate versions of the model with and without levels. Omitting hierarchical levels causes occupation-specific human capital to

be underestimated in the blue-collar occupation, and task-specific human capital to be underestimated in the white-collar occupation. In the model with levels, eliminating occupation-specific skill accumulation reduces mean wage level by 16.6%, while eliminating task-specific skill accumulation results in a 29.8% reduction.

Chapter four is coauthored with Jed DeVaro and Antti Kauhanen. We investigate the theory that promotion serves as a signal of worker ability using the German Socio-Economic Panel and the Confederation of Finnish Industries. Controlling for worker performance using bonus data and performance-related-pay, we find that promotion probabilities are increasing in educational attainment whereas wage increases from promotion are decreasing in educational attainment for some educational groups, with both results stronger for first than for subsequent promotions. Women have lower promotion probabilities than men, though this difference dissipates after first promotions. Evidence of promotion signaling is stronger for within-firm than for across-firm promotions.

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Manhattan, Kansas
Hugh Cassidy
October 18, 2013

To my parents, Keith and Elizabeth Cassidy

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Co-Authorship

The following thesis contains material co-authored by Jed DeVaro and Antti Kauhanen. All authors are equally responsible for the work which appears in Chapter 4 of this thesis.

Chapter 1

Introduction

The underlying themes of my dissertation are worker promotion and hierarchical level. In chapter two, I investigate the effects of job characteristics, as measured by the skill requirement of a job, on the probability that a worker receives a promotion. In chapter three, I estimate a structural occupational choice model where occupations are composed of hierarchical levels. Chapter four, which is co-authored with Jed DeVaro and Antti Kauhanen, tests the role of promotions in signalling worker ability using two European data sets.

Promotions are a common and important type of labor market mobility that McCue (1996) estimates contributes approximately 15% to wage growth over the worker's lifetime. It is not surprising, therefore, that there is a large literature that investigates promotions and the roles that they play. Theoretical models of promotions include three main frameworks. First, Lazear and Rosen (1981) model promotions as rewards in tournaments to induce worker effort.

Second, Waldman (1984) analyzes the effect of promotion as a signalling device, where outside firms see only a worker's hierarchical level (and thus a change in hierarchical level). Lastly, Gibbons and Waldman (1999) model promotions as the movement of workers to a job assignment with higher returns to ability. There have been numerous empirical studies that investigate the effects of job level on worker outcomes such as wages. Notably, Baker, Gibbs, and Holmström (1994) study a large U.S. financial services firm and document many stylized facts, including that wages are closely tied to job level, and changes in job level correspond to large changes in wages.

In chapter two, I investigate the determinants of promotions using the National Longitudinal Survey of Youth 1979. While there is a large literature in this area, it has focused mainly on the impacts of worker characteristics on promotion probability. The role of gender in promotion, investigated by Cobb-Clark (2001) and Pekkarinen and Vartiainen (2010), among others, has received particular attention.[1] While there has been some investigation of the effects of job characteristics on promotion, work in this area is minimal. This chapter partly addresses this gap by investigating how the skills required to perform a job impact the probability that a worker receives a promotion. I assign skill requirements to each Census occupation using data from the Dictionary of Occupational Titles. This provides a four-dimensional vector for each occupation that describes the Cognitive, Interpersonal, Manual, and Strength

[1] Other works including Pergamit (1999) and da Silva and van der Klaaw (2011) investigate the impact of promotion "type", e.g. one where the worker reports to a new supervisor versus has the same supervisor, and find that promotion type of also important to wage outcomes.

skill requirements in that occupation. I use this vector as my control for job characteristics, and run probit estimations to determine what effect skill requirements have on the likelihood that a worker receives a promotion.

I find that workers in more cognitively-intense occupations have significantly higher probabilities of receiving a promotion. Higher motor and strength skill requirements decrease the probability of a worker receiving a promotion, while the effect of the interpersonal skill is either negative or insignificant. In addition to impacting promotion receipt directly, the inclusion of these job characteristics changes the effects of other variables. The effect of education is reduced by 40% when skills are introduced, while a similar reduction occurs in the importance of the Armed Forces Qualification Test (AFQT) scores. I also find that omitting job characteristics causes the gender gap in promotion to be significantly understated: without skill requirement controls, women are 18.5% less likely than men to be promoted in a given year, while with skill requirements this difference rises to 29.5% points. I also find little evidence that skill requirement affects the wage change upon promotion, which might offset the impact of higher promotion probability. Overall, these results point to the importance of controlling for job characteristics when investigating promotion outcomes.

In chapter three, I investigate the role of hierarchical level on both occupational mobility and wage growth. I use the German Socio-Economic Panel (GSOEP), since it contains information about workers' hierarchical levels. I confirm previous studies that find job level significantly impacts worker wages. I also show that the probability of occupational change is higher for workers in the lowest hierarchical level. Lastly, workers who experience an unemployment spell and return to a lower hierarchical level than in their pre-unemployment job suffer significantly higher wage losses (roughly 10%) than those who return to the same or a higher level. The latter two empirical observations confirm the importance of level not only to overall wages, but also to job mobility and wage change. They also point to the existence of allocational frictions in the job search process, where workers are not free to move to their preferred occupation-level immediately. I investigate this possibility by estimating an occupational choice model where each occupation is composed of multiple levels and where workers must receive a job offer to change jobs.

In my model, hierarchical levels within an occupation are characterized by their task usages. These describe what types of activities a worker performs on the job. Poletaev and Robinson (2008) use tasks to investigate the transferability of human capital, and find that workers who are displaced and return to "closer" occupations (that is, occupations with similar task usages) suffer lower wage losses than those who return from unempoyment to "farther" occupations. Yamaguchi (2010, 2012), and Sanders (2012) use this measure of an occupation - the task usage vector - to replace occupations and simplify computational burden: instead of a worker searching over a large set of discrete occupations, they search over a small set of task usages. One of the drawbacks of current work, however, is that tasks are typically assigned based on a worker's occupation alone. This is because panel data sets with task usage information are rare. As a result, task usage by occupation is estimated in another data set and assigned to workers in the panel data set based on their occupation. However, Autor and Handel (2013) find that task usages vary significantly within occupations. Thus, assigning tasks based only on occupation misses potentially important task usage variation. Task usage data are taken from the German Qualification and Career Survey (GQCS), which contains the same job level variable as in the GSOEP. I show that task usage varies within an occupation by level, with cognitive task usage typically increasing with level while manual task usage declining. Since the GQCS contains both occupation and level information, I am able to assign task usages by both of these characteristics. This allows for at least some of the within-occupation variation described in Autor and Handel (2013).

Both task-specific and occupation-specific skills are acquired by the worker through learning-by-doing. While task-specific skills can be transferred to all occupation-levels, their usefulness depends on the task usage in a particular job. Occupation-specific skills can be transferred across levels within an occupation. I estimate my model using indirect inference. I am able to match the overall wage and occupational composition patterns in the data. I am also able to match the positive relationship between being in the lowest level and having a higher probability of changing occupations, and the negative impacts on wage changes from exiting unemployment to a lower level. I find that both sources of human capital accumulation are important but task-specific skill growth dominates. Counterfactual simulations where task-specific skill growth is eliminated cause a 32.7% decline in overall mean wage level, while eliminating occupation-specific skill accumulation results in only a 17.6% drop. Occupation-specific skills are more important to wage growth for the blue-collar occupation, while task-specific skills dominate in the white-collar occupation. I also run counterfactuals on the model version without hierarchical levels. Omitting levels significantly understates the importance of occupation-specific skills to wage growth for the blue-collar occupation, while also understating the importance of task-specific skills for the white-collar occupation.

Chapter four is co-authored with Jed DeVaro and Antti Kauhanen. In this chapter, we test the theory that promotions serve as a signal about a worker's ability. In an environment where information is asymmetric and the worker's current employer has more information about a worker's ability level than outside employers, a promotion sends a signal to outside firms that the worker is of high ability. This notion was first described by Waldman (1984), who shows that when a worker is promoted their employer must increase their wage to avoid having them bid away by an outside firm. This helps to explain the large wage gains that typically accompany promotions. However, since promotions require the firm to increase wages they are costly. As a result, some workers that would be more productive if they were moved to a higher level are not promoted, as the firm would lose their informational advantage, and so there is an inefficient allocation of workers across levels.

DeVaro and Waldman (2012) extend this framework by including a worker characteristic, such as education, that is publicly observable and correlated with the worker's innate ability. Two key findings result: (1) promotion probability is increasing in education, even conditional on ability; and (2) wage gains from promotion are decreasing in education level, again conditional on ability level. Also, these results dissipate after the worker receives their first promotion. The intuition beyond these results is that the promotion of a less educated worker is more of a surprise to outside firms, who had a low initial belief about their ability, than the promotion of a more educated worker. This requires the current firm to bid up the less educated worker's wage upon promotion more so than the more educated worker to avoid turnover, making the promotion of less educated workers more costly even controlling for ability. This reduces the promotion probability of less educated workers. DeVaro and Waldman (2012) then test these predictions using data from the U.S. firm analyzed by Baker, Gibbs, and Holmström (1994), and the results largely confirm the theory. However, since this is only a single firm, generalizing the results is problematic.

We extend the tests performed by DeVaro and Waldman (2012) by using two large-scale, nationally-representative, European panel data sets: the GSOEP and the Confederation of Finnish Industries. One of the difficulties in using this type of data is that information about worker performance is typically unavailable. We address this problem by running regressions of performance-related-pay and bonus data on worker, firm, and job characteristics. Whatever we are not able to explain by observable characteristics, i.e. the residual of these regressions, we assume is the unobserved worker performance and we use these values as our performance measures. We test the first empirical prediction, that education is positively related to promotion receipt, by performing probit estimations which include our performance measure. The second empirical prediction, that conditional on promotion, more educated workers receive lower wage gains, is tested using a wage change regression, again controlling for performance using our inferred measure. Consistent with the theory described in DeVaro and Waldman (2012), we find that promotion probabilities are increasing in educational attainment, whereas wage increases from promotion are decreasing in educational attainment for some educational groups. Both of these results are stronger for first than for subsequent promotions. We also find that women have lower promotion probabilities than men, though this difference dissipates after the first promotion. Since we are able to follow workers after they leave their current firm, and our hierarchical level assignment procedure is not firm-specific, we can separately investigate within-firm versus across-firm promotion. We find that evidence of promotion signaling is stronger for within-firm than for across-firm promotions.

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Chapter 2

Worker Promotion and Occupational Skill Requirement

2.1 Introduction

This chapter estimates the impact of occupational characteristics on the probability that a worker receives a promotion. Specifically, it examines the effects of occupational skill requirements, as measured by the requirements of cognitive, interpersonal, motor, and strength skills, on promotion receipt. I find that the skills required in an occupation do, in fact, have a significant effect on the probability that a worker receives a promotion. In particular, workers in occupations with higher cognitive skill requirement have a significantly higher probability of receiving a promotion.

Promotions within an employer are an important source of wage growth for workers. McCue (1996) estimates that promotions account for up to 15% of life-cycle wage growth.[1] As a result, there is a large literature studying both the determinants and effects of promotions on workers. The current literature has focused mainly on the effects of worker characteristics and, to a lesser extent, firm characteristics, on the likelihood of promotion. Particular focus has been given to the role of gender in the promotion process, while little attention has been paid to the effects of job characteristics on a worker's promotion probability.

I use the skills required to perform a job as measures of a job's characteristics. The occupational skill requirement measure employed here, used in both Ingram and Neumann (2006) and Poletaev and Robinson (2008), incorporates a measure of the skills required to perform a job from the Dictionary of Occupational Titles (DOT). Every DOT job title consists of a large, 63-element vector of characteristics, and includes variables such as numerical aptitude, strength, eye-hand-foot coordination, etc. Each measures the importance of that particular characteristic in performing a given job. Using Principal Component Analysis (PCA), I reduce this vector to four components: cognitive, interpersonal, motor and strength. DOT to three-digit Census occupation crosswalks are used to move from DOT job titles to both 1970 and 2000 Census occupation codes. The result is that each three-digit Census occupation is assigned a 4-dimensional skill vector measuring the skill requirements of that job.

I combine these skill requirements with the National Longitudinal Survey

[1] Cobb-Clark (2001) estimates the wage gain at around 30% for promotions alone in a sample of young workers.

of Youth 1979 (NLSY79). The advantage of this data set is twofold: first, as a panel data set with rich data on workers, it allows me to control for individual worker effects; and second, for certain years (1988-1990 and 1996-2008) it includes a question that asks if the worker has received a promotion at any job since the previous interview. These features have motivated other studies, such as Pergamit (1999) and Cobb-Clark (2001), to use this data set to study promotions. However, these papers consider only the 1988-1990 timeframe. This narrow timeframe restriction is especially limiting for the NLSY79 since the survey's participants were between the ages of 14-22 in 1979; thus, studying a small number of years will miss potentially important life-cycle effects due to the respondents' narrow age range.

A probit model is employed to estimate the effects of job skill requirements, as well as other variables, on the probability that a worker receives a promotion between two interviews. As the NLSY79 is annual during the 1988-1990 period, and biannual in the 1996-2008 period, I perform this analysis separately for these two time periods. I also estimate the model for the whole sample as well as separately for men and women. The results indicate that the skill requirements of a job do in fact have significant impacts on a worker's probability of promotion. Higher levels of cognitive skills have a positive effect for men as well as for women in both of the sampling periods. The other three skill measures - interpersonal, motor and strength - have negative effects on promotion, though their effects are not always significant.

Table 2.1: Skill Levels and Promotion: Financial Manager versus Building Manager

	Financial Manager	Building Manager	Difference	Marginal Effect
Cognitive	12.081	9.996	2.085	0.033
Interpersonal	3.789	3.009	0.780	−0.009
Motor	4.557	5.265	−0.708	0.0003
Strength	.035	.285	−0.250	0.022
Total				4.63%

Promotion probability difference from skill level differences, Financial Manager versus Building Manager.

The effects of skill requirements on promotion are non-trivial in magnitude. For example, consider two white-collar occupations, Financial Manager and Building Manager, both of which are classified in the same one-digit occupation coding group. Table 2.1 shows the skill levels for these two groups as well as the marginal effects of their skill differences on the probability of promotion.[2] Overall, as a result of their differing occupational skill requirements, a Financial Manager has a predicted promotion rate which is 4.63 percentage points higher than a Building Manager, which corresponds to a roughly 25% higher overall promotion rate. Though these occupations have fairly similar skill requirement vectors compared to the overall distribution, the relatively small differences between them nonetheless generate a large gap in the predicted promotion rates. As promotions are associated with substantial increases in wages, 9.6% vs 2.4% for promoted vs non-promoted workers in the data used in this chapter, a 4.63% difference in the probability of promotion per year has a significant impact on a worker's expected future earnings.

[2]Skill requirements for these occupations are taken for men in the 1970 coding period. Marginal differences taken from the estimates in Section 6.2. See Table 2.14.

Apart from the skill requirement levels' direct effects on the probability of promotion, their inclusion also changes the effects of other non-skill variables, often substantially. In both survey periods, the lower promotion probability for high-school versus college graduates is reduced by roughly 40% after skills are included. A similar reduction occurs in the importance of Armed Forces Qualification Test (AFQT) scores. These results indicate that at least part of the impacts of some individual characteristics, such as education and intelligence, on the receipt of promotion act through their impact on the individual's job type. College graduates and those with higher AFQT scores tend to be employed in higher-cognitive jobs than high-school graduates and those with lower AFQT scores, and a higher cognitive skill requirement is associated with a higher promotion probability. Though the selection of a worker into a job is important, individual characteristics persist even after controlling for skills, which indicates that worker heterogeneity plays a role in the promotion process.

This chapter is organized as follows. In Section 2.2, I describe the existing literature, both on promotions and on occupational skill requirements. Section 2.3 describes the data used. Section 2.4 details the procedure for calculating the skill requirement vectors, and motivates the relevance of the derived skill measures by considering their relationship with wages. Section 2.5 estimates the effects of skills on promotions, and discusses the results. Section 2.6 concludes. Supplementary tables are presented in Appendix A.1.

2.2 Existing Literature

The importance of promotions has been recognized in the economics literature for some time, and there are large bodies of both empirical and theoretical work on the topic. Three main theories about the effects and uses of promotions exist: 1) they serve as rewards in tournaments to induce effort (Lazear and Rosen (1981)); 2) they send a signal to outside employers about a worker's ability (Waldman (1984)); and 3) promotions are a means of optimally allocating a worker to the "correct" production technology, i.e. level, as a result of learning about a worker's ability and/or a worker's accumulation of human capital (Gibbons and Waldman (1999)). While these three models of promotion are not necessarily mutually exclusive, and a role for each is almost certainly present to some extent, the Gibbons and Waldman (1999) model is the one that has become the standard in the literature for analyzing within-firm promotion dynamics.

Empirically, the literature can be broadly divided into studies that focus on a particular firm, and those that look at cross-firm data. The seminal contribution in the empirical literature, Baker, Gibbs, and Holmström (1994), is a case-study that examines a large U.S. financial services firm. Describing what would become many of the stylized facts in the literature, Baker, Gibbs, and Holmström (1994) document significant wage gains from promotion, evidence for fast-track promotions, and the importance of job level to wages. Several subsequent studies, including Treble, Van Gameren, Bridges, and Barmby (2001) and Dohmen, Kriechel, and Pfann (2004), perform similar analyses on British and Dutch firms, respectively, largely confirming results from Baker, Gibbs, and Holmström (1994).

Pergamit (1999) and Cobb-Clark (2001) extend the analysis in Baker, Gibbs, and Holmström (1994) beyond a single firm by studying promotions using the NLSY79. Using data from the 1988-1990 survey period these studies examine both the determinants and outcomes of promotions.[3] Cobb-Clark (2001) focuses on the role of gender in the promotion process, and finds that women are less likely to be promoted and they face higher promotion standards than men; however, the wage growth from promotion for women is larger than for men. Pergamit (1999) examines how the type of promotion, i.e. reports to a higher supervisor or has an increase in responsibilities, affects the determinants and outcome of promotion.

A major limitation of the current work has been its sparse controls for job characteristics. The question of how promotion probabilities are affected by the type of job a worker is performing has not been adequately addressed. While Cobb-Clark (2001) notes the importance of occupation group for promotion receipt, there is substantial variation within any given one-digit occupation code in the skills required to perform a job.[4] This chapter more precisely controls for the characteristics of a job by including these skills, and shows that not only

[3]Francesconi (2001) and Booth, Francesconi, and Frank (2003) use British Household Panel Survey data and perform similar studies on the determinants and outcomes of promotions in Britain.

[4]While the variances in skills within one-digit occupation groups are, not surprisingly,

do they have statistically significant effects on promotion probabilities themselves, but their inclusion also affects the impacts of other variables on the likelihood of promotion.

The process used to measure an occupation's skill requirements derives from work by Ingram and Neumann (2006) and Poletaev and Robinson (2008). Both of these papers utilize the DOT measure of a job's skill requirements, which, using factor analysis, are reduced to a four-dimensional vector. In Ingram and Neumann (2006), these skills are classified as intelligence, fine motor, coordination and strength, while the four skills in Poletaev and Robinson (2008) are denoted as general intelligence, fine motor, strength and gross motor, and visual skills.[5] Based on work suggesting a close match between a job's skill requirements and the worker's actual skill level,[6] the skill requirement levels derived from the DOT can then be interpreted as appropriate measures of a worker's skill level. As this chapter uses the DOT data to measure features of the job, not the worker, the link between the job's skill requirements and the worker's skill level is less important than in other studies.

Instead of the factor analysis approach for deriving skill requirements vectors, this chapter uses the principal component analysis technique employed by Bacolod and Blum (2010) and Yamaguchi (2010a). This method requires a

smaller than the population, they are nonetheless large. See Tables A-1 and A-2 in the Appendix, which show the summary statistics for skill levels by white-collar, blue-collar and one-digit occupation group.

[5] Since a single DOT characteristic can contribute to several skills, and factor analysis is insensitive to rotations, it is difficult to categorize these skills precisely. However, examination of the main characteristics contributing to the skills yields these interpretations.

[6] See Albrecht and Vroman (2002) and Wong (2003)

priori assumptions about which DOT characteristics contribute to which skills, but allows for correlations to exist between skill levels.[7] Furthermore, imposing which characteristics contribute to which skills clarifies their interpretation. While neither of these methods is clearly superior to the other, I choose the PCA approach for both the ease of interpretation and to allow for skill correlations.

2.3 Data

2.3.1 NLSY79

Worker data come from the National Longitudinal Survey of Youth 1979. This is a panel data set with rich information about a cohort of individuals who were between the ages of 14 and 22 in 1979. These data are useful for this analysis since there are two periods, 1988-1990 and 1996-2008, during which the respondent is asked if he or she received a promotion since the previous interview. The definition of promotion used here is self-reported, and is not based on a measured change in a worker's tasks.[8] While the self-reported nature of the promotion variable is of potential concern, it has the advantage of not having to

[7] There are, in fact, strong correlations between the factors that are derived. See Table 2.5.

[8] The NLSY79 also includes questions for whether the worker's responsibilities increased or if they are reporting to a higher supervisor as a result of their promotion. Both Cobb-Clark (2001) and Pergamit (1999) cite the importance of the type of promotion, i.e. with or without an increase in responsibility and with or without a change in supervisor, for their results. Qualitatively, the results are quite similar using the supervisor or responsibility increase promotion definitions instead and, as such, I restrict attention to the most general promotion definition for the remainder of the paper.

rely on either wage or occupational changes to define a change in hierarchical level.[9]

Spurious occupation changes between periods is a well-known issue plaguing many panel data sets, the NLSY79 included. As skill requirement levels are linked to occupations, these spurious changes are of concern in this analysis. Some papers, including Neal (1999) and Pavan (2011), assume that all within-firm occupation changes are miscodings. However, as I am interested specifically in promotions, and many promotions would reasonably involve changes in occupations, this assumption is not appropriate in this case. Instead, I follow Yamaguchi (2010a) and consider an occupation change as genuine only if the worker does not return to the previous occupation during the current firm-employment spell. For example, if a worker begins in occupation A in year 1, moves to occupation B in year 2, then back to occupation A in year 3, I assume the worker is in occupation A for all three periods, and thus no change in occupation has occurred. This correction procedure results in a 31% reduction in the number of occupation changes.[10]

[9]Frederiksen, Halliday, and Koch (2010), for example, relies on changes in the occupation code to denote a promotion. However, as is discussed below, only 39% of promotions in the NLSY79 correspond with occupation changes, while data from the German Socio-Economic Panel suggests that only roughly 20% of promotions in Germany correspond to occupation changes.

[10]Yamaguchi (2010a) cites a reduction of roughly 40% in occupation changes. The difference is probably due to sample period: occupation coding in later years, especially during the 2000 Census occupation coding period, seems to be better encoded, and the number of occupation changes occurring after 1994 drops by 16%, while after 2000 it drops only by 5.7% as a result of this procedure. This difference is likely caused by the NLSY79 survey becoming more dependent in later survey years, and explicitly asking for a worker's occupation again only if it is different than in previous years.

Table 2.2: Summary Statistics

	All		Men		Women	
	Mean/%	s.d.	Mean/%	s.d.	Mean/%	s.d.
Age (years)	34.36	6.69	34.19	6.65	34.60	6.72
Black	0.27	0.45	0.25	0.44	0.30	0.46
Hispanic	0.17	0.38	0.18	0.38	0.17	0.38
Two-year Interviews	0.65	0.48	0.64	0.48	0.65	0.48
2000 Codes	0.24	0.43	0.23	0.42	0.25	0.43
Human Capital						
Tenure (years)	5.55	5.44	5.58	5.52	5.50	5.34
Experience (years)	12.79	4.81	13.03	4.81	12.48	4.79
AFQT 1	0.16	0.37	0.18	0.38	0.13	0.34
AFQT 2	0.22	0.41	0.20	0.40	0.24	0.43
AFQT 3	0.20	0.40	0.18	0.39	0.23	0.42
AFQT 4	0.21	0.41	0.21	0.41	0.22	0.41
AFQT 5	0.21	0.40	0.22	0.42	0.18	0.38
High School	0.47	0.50	0.52	0.50	0.39	0.49
Job						
ln Wage (cents/hr)	6.65	0.46	6.72	0.47	6.55	0.44
Overtime (# hours/week)	1.10	3.69	1.29	4.07	0.83	3.09
Union	0.18	0.39	0.20	0.40	0.16	0.37
Promotion	0.17	0.38	0.17	0.38	0.17	0.38
# promotions	0.42	0.77	0.43	0.80	0.41	0.74
Firm Size						
Small Firm (<100 employees)	0.57	0.49	0.61	0.49	0.53	0.50
Medium (100-500)	0.24	0.43	0.22	0.41	0.26	0.44
Large(>500)	0.19	0.39	0.17	0.38	0.21	0.41
Occupation						
Blue-Collar	0.46	0.50	0.60	0.49	0.26	0.44
Managers and Prof.	0.16	0.36	0.15	0.35	0.17	0.38
Sales	0.04	0.19	0.04	0.20	0.04	0.19
Admin. and Support	0.17	0.38	0.07	0.26	0.31	0.46
Service	0.09	0.29	0.07	0.25	0.13	0.34
Precision Craft	0.17	0.38	0.27	0.44	0.03	0.18
Operators and Laborers	0.19	0.39	0.26	0.44	0.10	0.30
Technicians	0.18	0.38	0.14	0.35	0.22	0.41
Occupation Change	0.20	0.40	0.21	0.40	0.20	0.40
Observations	39,546		22,720		16,826	

Note 1: If units specified, means presented; otherwise, percentages given

Note 2: Statistics of final estimation sample only

Overall, after implementing the preceding correction procedure, 22% of individuals change occupations between two survey periods.[11] Among promoted workers, this value is 39%. Also, while occupation changers experience greater wage growth than non-changers, this difference is due to the higher promotion rate among occupation changers. In fact, as Table 2.3 indicates, non-promoted occupation changers have somewhat lower wage growth than non-promoted

Table 2.3: Log Wage Changes by Event Type

	All Mean/s.d.	Men Mean/s.d.	Women Mean/s.d.
Promotion	9.50	9.26	9.83
	(21.77)	(21.67)	(21.90)
Occupation Change	4.69	4.27	5.27
	(23.73)	(24.42)	(22.73)
Promotion/Occupation Change	10.80	9.94	11.87
	(21.97)	(21.33)	(22.71)
Promotion/No Occupation Change	8.76	8.89	8.58
	(21.62)	(21.85)	(21.29)
No Promotion/Occupation Change	1.99	1.91	2.10
	(23.97)	(25.23)	(22.06)
No Promotion/No Occupation Change	2.58	2.19	3.10
	(22.53)	(23.39)	(21.33)
Observations	39,546	22,720	16,826

Note: 100*Log wage changes; wages in cent/hr, 1983 dollars.

occupation stayers.

I consider workers who have stayed with the same firm for at least two consecutive survey periods during the years when promotion data are available, from 1988-1990 and 1996-2008. As the NLSY79 is biannual after 1994, I have a total of ten years of promotion data. Values included in the estimation are those that occur in the initial period. Thus, the results that are obtained reflect the probability of a worker receiving a promotion between the current and subsequent interview periods. There are a total of 113,520 instances of a worker staying with the same firm for two consecutive survey periods. I consider only full-time workers, defined as those working 35 hours per week or more, leaving 88,724 observations. Demotions are dropped,[12] eliminating 1379 observations.

[11]This figure includes the final estimation sample, excluding the 2000-2002 transition period, since occupation change is impossible to determine due to the change in Census occupation coding scheme.

[12]Demotions are a rare event in this data; each year roughly 2.3% of workers are demoted, compared to 14% for promotions.

I clean wage data by dropping observations with wages either in the current or pre-promotion year lower than \$3.00/hr, and I trim the top of the wage distribution at the 99% level. I also trim wage change observations at the 1% and 99% levels. This leaves 46,104 observations.[13] Other missing data, such as missing tenure and firm size information, eliminate 6558 observations. In total, I am left with 39,546 observations - 13,992 in the one-year (1988-1990) sampling period, and 21,468 in the two-year (1996-2008) sampling period. These data represent 8413 individuals and 15,707 worker-firm spells. Table 2.2 shows summary statistics for this sample. There are 6821 promotions and 8069 occupation changes, resulting in promotion and occupation change rates of 17.3% and 20.4% respectively. Roughly 39% of promotions coincide with occupation changes. These values vary little by gender.

In 2002, the NLSY79 changed from the 1970 Census occupation coding scheme, which had been used since 1979, to the 2000 Census coding scheme. Unfortunately, there exists no one-to-one crosswalk between these two methods of coding occupations. As a result, skill levels derived during these different periods may not be fully comparable. This issue is discussed further in Section 2.4.2. In the following two sections, I describe the process by which each three-digit Census occupation code is assigned a four-dimensional skill requirement vector.

[13] All wage data are in 1983 dollars

2.3.2 Dictionary of Occupational Titles

One of this chapter's contributions is to incorporate a detailed description of a job, i.e. the skills required to perform that job, into the analysis of promotion receipt. The importance of occupational skill requirements is supported by Poletaev and Robinson (2008), which provides evidence that human capital is largely specific to a small number of basic skills, as opposed to being primarily firm- or industry-specific. The source of these skill requirements is the Dictionary of Occupational Titles (DOT) and a special version of the 1971 Current Population Survey (CPS). The DOT assigns each of its over 12,000 job titles a vector of characteristics, which measures the requirements of the job. The first component of the DOT code is the worker functions ratings, which describe a job's complexity of interaction with data, people and things. The DOT code definition trailer includes information on several other groups of characteristics, including measures for aptitudes, general educational development and temperament. Each of these groups contains several characteristics. For example, the aptitudes group includes a numerical variable describing the degree of numerical aptitude needed to perform a job.[14] Together, these provide a comprehensive vector of characteristics describing each DOT job title.

Since the NLSY79 contains only Census occupation coding, and not DOT coding, it is necessary to convert the DOT job title vector of characteristics

[14] As an example, the numerical aptitude variable is measured from 1-5, where: 1 = top 10% of population; 2 = top 1/3, excluding the top 10%; 3 = middle 1/3; 4 = bottom 1/3, excluding bottom 10%; and 5 = bottom 10%.

into a Census occupational vector of characteristics. For each job title, the DOT master file includes the corresponding three-digit Census occupational code. However, as there are many more DOT job titles than occupations, some occupations have multiple job titles mapping into them. Two DOT job titles mapping to the same Census occupation code may have different characteristic vectors; therefore it is necessary to weight these job titles correctly to properly calculate an occupation's characteristic vector. To do this, a measure for the fraction of employment in each DOT job title is needed. This construction of weights is made possible by a unique data set, a special version of the Current Population Survey in 1971, in which each of the 60,441 workers are coded with a DOT job title. Using these data, it is therefore possible to assign employment weights to each DOT job title. These weights are then used when assigning characteristic vectors to each three-digit Census occupation code.

Since the employment shares in each DOT job title may differ by gender, this crosswalk procedure is done separately for men and women. As a result, men and women have, often significantly, different skill requirement vectors for the same occupation code. Also, as there is no way to easily move between the 1970 to 2000 Census occupation coding schemes, the DOT to Census conversion is also done separately for this occupational group. To convert from DOT to 2000 Census schemes, the weighted crosswalk approach, described in more detail in Robinson (2011), is used. This crosswalk is developed in two parts. First, a Standard Occupational Classification (SOC) to DOT crosswalk is combined with a SOC to Census 2000 crosswalk to generate a DOT to 2000 Census crosswalk. However, some occupations are missing from this crosswalk. To fill in these gaps, a crosswalk developed from dual-coded samples is used.

2.4 Skill Requirements

Having assigned a vector of characteristics to each Census occupation, the next step is to reduce the size of this vector to a more manageable, four-dimensional vector of skill requirements. The following section describes this process.

2.4.1 Principal Component Analysis

Principal Component Analysis is used to reduce the size of the 63-element vector of characteristics. A priori assumptions about which characteristics contribute to which skills are needed using the PCA approach, but it allows for correlation between the estimated skills. Following Bacolod and Blum (2010) and Yamaguchi (2010a), I assume the existence of four underlying skills: cognitive, interpersonal, motor and strength. I then assume that a subset of the DOT characteristic vector contributes to each of these skills. This assumption simplifies the interpretation of the skills calculated, since the researcher knows which characteristics are contributing to them. It contrasts with the factor analysis approach used in Ingram and Neumann (2006) and Poletaev and Robinson (2008) where a single factor can contribute to multiple skills, making the interpretation of what each skill is measuring more difficult.

I use the same skill assignment as Bacolod and Blum (2010) and Yamaguchi (2010a). The DOT characteristics that measure the cognitive skill requirement of a job are: complexity of the interaction with data, three general educational development variables (reasoning, mathematical, and language), and three aptitude factors (general reasoning ability, verbal, and numerical). The interpersonal skill is calculated using: complexity of the interaction with people, adaptability to influencing people (influ), adaptability to accepting responsibility for direction (dcp), and adaptability to dealing with people (depl). Motor skill is measured from variables: complexity of the interaction with things, seven aptitudes (motor coordination, finger dexterity, manual dexterity, eye-hand-foot coordination, spatial perception, form perception, and color discrimination), and setting limits, tolerance or standards. The last skill requirement, strength, is measured with a single characteristic, strength.[15]

I perform the PCA separately for men and women and for the 1970 and 2000 Census occupation coding periods, using the entire NLSY79 sample.[16]

[15]See Bacolod and Blum (2010) Appendix A for more detailed descriptions of each of these variables.

[16]I use the entire sample period to generate the factor loadings, from 1979-2000 for the 1970 codes, and 2002-2008 for the 2000 codes. However, summary statistics and other results are presented for only the final estimation sample.

The purpose of PCA is to represent a higher-dimensional vector with a lower-dimensional vector of “components”, while maintaining as much of the variation present in the original data as possible.[17] The procedure involves calculating the eigenvector decomposition of the largest eigenvalue of either the covariance or correlation matrix. The choice of method is potentially important, since the calculated factor loadings are sensitive to units as well as to differences in the variances of characteristics. This chapter uses the correlation matrix approach, since it is advised in the presence of large differences in variance between characteristics.[18,19,20] The results, however, change little when the covariance method is used instead.

Table 2.4 reports the factor loadings for men and women for the two coding schemes. The pattern of factor loadings is similar to Bacolod and Blum (2010), but not surprisingly differs from Yamaguchi (2010a) where the covariance method is used. Using these factor loadings, skill requirements are assigned to each occupation in my data. Summary statistics for skill levels, male and female, are reported in Table 2.7, while correlations between the skills are

[17]See Jolliffe (2002) for additional details.

[18]See Jackson (1991), pp 64-65

[19]For example, the data variable has a standard deviation of 1.58, while the numerical aptitude variable's standard deviation is only 0.65. Such large differences in the characteristics' variations advises against using the covariance matrix method.

[20]Yamaguchi (2010a) uses the covariance method, while Bacolod and Blum (2010) seem to use the correlation matrix

Table 2.4: Factor Loadings

	1970		2000	
	Men	Women	Men	Women
Cognitive				
data	0.373	0.378	0.368	0.368
gedr	0.387	0.384	0.391	0.392
gedm	0.378	0.380	0.376	0.371
gedl	0.385	0.384	0.388	0.390
aptitudg	0.382	0.386	0.381	0.390
aptitudv	0.377	0.383	0.381	0.389
aptitudn	0.363	0.349	0.360	0.343
Interpersonal				
people	0.560	0.583	0.568	0.590
tempi	0.403	0.491	0.327	0.399
tempp	0.532	0.402	0.561	0.471
tempd	0.491	0.508	0.506	0.520
Motor				
things	0.400	0.409	0.393	0.381
aptitudk	0.384	0.393	0.385	0.402
aptitudf	0.372	0.413	0.366	0.416
aptitudm	0.354	0.357	0.373	0.365
aptitude	0.109	0.031	0.183	0.123
aptitudc	0.272	0.224	0.277	0.260
aptitudp	0.344	0.405	0.328	0.360
aptituds	0.340	0.295	0.341	0.293
tempt	0.330	0.280	0.301	0.300

Note: 1970 codes: prior to 2002; 2000 codes: 2002 to 2008

reported in Table 2.5.[21,22] In general, the jobs women hold have higher cognitive and interpersonal skill requirements than the jobs men hold, and lower motor and strength requirements.

There exists a strong, positive correlation between cognitive and interpersonal skills, a more weakly positive motor and strength correlation, and negative correlations with strength and both cognitive and interpersonal skills. Lastly, Table 2.6 reports summary statistics for skill level changes, both for

[21] Skill correlations and summary statistics are reported only for the final sample used in estimation.

[22] Separate correlations for men and women are shown in Appendix Tables A-3 and A-4. While similar overall, the correlations between strength and the other three skills are significantly weaker for women than men.

Table 2.5: Skill Level Correlations

	Cognitive	Interpersonal	Motor	Strength
Cognitive	1.00			
Interpersonal	0.69	1.00		
Motor	-0.06	-0.45	1.00	
Strength	-0.63	-0.51	0.27	1.00

Table 2.6: Skill Changes

	All Mean/s.d.	Promoted Only Mean/s.d.
Cognitive Change	0.28	0.72
	2.43	2.47
Interpersonal Change	0.16	0.39
	1.31	1.46
Motor Change	−0.11	−0.29
	1.96	1.98
Strength Change	−0.01	−0.03
	0.18	0.18
Observations	8,069	2,476

Note: Only occupation changes included; 2000-2002 omitted

Table 2.7: Skill Levels

	All Mean/s.d.	Men Mean/s.d.	Women Mean/s.d.
Cognitive	8.67	8.49	8.92
	2.41	2.50	2.26
Interpersonal	2.14	1.97	2.37
	1.32	1.27	1.35
Motor	6.78	7.01	6.47
	1.72	1.77	1.60
Strength	0.32	0.39	0.22
	0.21	0.20	0.17
Observations	39,546	22,720	16,826

all occupation changes and for only the promoted group.[23] A clear pattern emerges: cognitive and interpersonal skills tend to increase with occupation change, while motor and strength decline. Promotions result in especially large increases in cognitive and interpersonal skill levels and decreases in motor and strength skill levels. This pattern accords with the intuition that promotions move workers into more managerial and administrative roles, where cognitive and interpersonal skills are especially important.

2.4.2 1970 vs 2000 Census Occupation Codes

The NLSY79 records a Census occupation code for each job. From 1979 to 2000, inclusive, these occupations are encoded using the 1970 Census occupation codes, while from 2002 to 2008 the NLSY79 uses the 2000 Census occupation codes. The differences between the 1970 and 2000 coding schemes are substantial. In fact, there is no clear crosswalk between the 1970 to 2000 codes for many occupations. Earlier Census occupation codes, including the 1970 codes, are based on a hierarchical structure, whereas the 2000 occupational codes are organized by "job families", grouping workers by the output produced, not by services provided.[24]

As the central focus of this chapter is the effect of skills on promotion receipt, the comparability of the 1970 and 2000 occupation codes is important. I first compare the distribution of worker skill requirement levels in years with 1970 codes versus 2000 codes, shown in Table 2.8. While the 2000 occupation codes yield higher levels of cognitive and interpersonal skills, and lower levels of motor and strength, these changes may be driven by life cycle effects, which

[23] Only occupation changers are included since skills change only if occupation changes, excluding the 2000-2002 transition.

[24] See Scopp (2003) for discussion.

Table 2.8: Skill Levels: 1970 and 2000 Codes

	1970			2000		
	All Mean/s.d.	Men Mean/s.d.	Women Mean/s.d.	All Mean/s.d.	Men Mean/s.d.	Women Mean/s.d.
Cognitive	8.65	8.47	8.90	8.75	8.56	8.99
	2.38	2.47	2.24	2.49	2.60	2.32
Interpersonal	2.08	1.92	2.32	2.31	2.13	2.54
	1.26	1.20	1.31	1.48	1.47	1.45
Motor	6.80	7.01	6.51	6.71	7.00	6.34
	1.69	1.72	1.60	1.80	1.91	1.58
Strength	0.32	0.39	0.21	0.31	0.38	0.22
	0.20	0.20	0.16	0.22	0.21	0.19
Observations	30,049	17,462	12,587	9,497	5,258	4,239

Note: 1970 codes: prior to 2002; 2000 codes: 2002 to 2008

correspond to changes described in Table 2.6. It is more appropriate, therefore, to consider skill levels in periods directly surrounding the coding scheme change, from 1998 to 2002. A large difference in the levels before and after the coding change would imply the existence of a significant break that results from a move to the new coding scheme. Table 2.9 shows the skill level distributions around the time of transition. From 2000 to 2002, cognitive skill levels drop somewhat, which is contrary to their usual upward trend, though the drop, less than a twentieth of a standard deviation, is minor. The increase in interpersonal skills is slightly greater than typical, though as with cognitive skills the difference is small, while motor and strength levels change little. Thus, there does not appear to be a significant break in the overall distributions of skills around the change in coding scheme.

Though the overall skill level distributions do not change significantly between the coding periods, there could still be significant reassignment of workers to different skill requirement levels that nonetheless results in an overall

Table 2.9: Skill Levels: 1970 and 2000 Codes, Transition Years

	1970		2000	
	1998 Mean/s.d.	2000 Mean/s.d.	2002 Mean/s.d.	2004 Mean/s.d.
Cognitive	8.81	8.84	8.73	8.74
	2.41	2.39	2.50	2.47
Interpersonal	2.20	2.23	2.31	2.29
	1.31	1.31	1.48	1.46
Motor	6.68	6.66	6.72	6.72
	1.68	1.68	1.80	1.81
Strength	0.31	0.31	0.31	0.31
	0.20	0.20	0.22	0.22
Observations	3,990	3,864	3,273	3,062

negligible net effect on skill level distributions. I investigate this possibility by examining the changes in skill levels between years, again surrounding the change in coding that occurs in 2002. For years before and after 2000-2002, only workers who change occupations have a change in their skill requirement levels, since these levels are associated with their occupation. However, between 2000 and 2002, all workers' skill levels can change, as their occupations necessarily change between these two years. If there is a significant break between the coding schemes, this will result in a greater variance in the skill change levels between 2000 and 2002 than between other years.

Table 2.10 shows the distribution of skill requirement changes around the transition period. As expected, the variances in the skill level changes are greater during the transition period than during other periods, since each worker has, to some degree, a change in skill level. However, these variances are lower than "genuine" occupation changes in either of the coding periods, as shown in Table 2.6. Thus, while the amount of reassignment from the coding

Table 2.10: Skill Level Changes: 1970 and 2000 Codes, Transition Years

	1970		Transition	2000	
	1996 Mean/s.d.	1998 Mean/s.d.	2000 Mean/s.d.	2002 Mean/s.d.	2004 Mean/s.d.
Cognitive Change	0.09	0.07	0.11	0.02	0.07
	1.23	0.85	1.41	0.83	0.94
Interpersonal Change	0.04	0.04	0.18	0.02	0.05
	0.66	0.46	0.95	0.57	0.64
Motor Change	−0.03	0.00	0.08	−0.01	−0.03
	1.04	0.75	1.26	0.64	0.73
Strength Change	−0.00	−0.00	−0.01	−0.00	−0.01
	0.09	0.06	0.12	0.06	0.07
Observations	4,117	3,990	3,864	3,273	3,062

change is not as significant as if workers were all changing occupations during either coding period, there does appear to be a non-trivial amount of change occurring.

Robinson (2011) examines involuntary mobility and uses skills to calculate a distance between two occupations related to the differences in their skill requirements. The issue of the comparability between the 2000 Census occupation coding and earlier schemes is also present in this work. To compare these schemes, an expected distance measure from a worker randomly moving from one occupation to another is calculated for the different coding periods. The result is that, for either coding period, the distances from random mobility have nearly identical distributions. This indicates that there is no break between the coding periods in terms of distance, which provides evidence of the comparability of skills derived from these separate coding schemes.

The results with regard to the comparability of the different coding periods are mixed. To avoid potential issues that might arise with combining these periods, I estimate the effects of skill levels separately for the 1970 and 2000 coding periods.

2.4.3 Skill Requirement Levels and Wages

In order to demonstrate the importance of the estimated skill requirement levels, I perform a regression of the worker's log hourly wage on their occupational skill requirements. While the estimations include human capital variables (experience, tenure, and education level), demographic variables (age, sex, race, and AFQT scores), and industry and year controls, for brevity, only skill requirement levels are shown.[25] This is performed for the entire sample, as well as for men and women separately. As this analysis does not rely on promotion data, the entire NLSY79 panel is used, from 1979 to 2008. Table 2.11 shows the results.

The skill requirement levels have a statistically significant effect on wages, and alone they can explain a large fraction of wage variation. The cognitive skill has a consistently positive effects on wages, while interpersonal and motor have consistently negative effects. The strength skill, though positive overall, has a negative effect for men but a positive effect for women. In addition to this difference in sign between men and women, the effects also vary in magnitude by gender. Overall, women's wages appear to be more sensitive to the skill requirements of the job, with the absolute value of each coefficient higher for

[25] Again, for simplicity and brevity, I ignore the potential incomparability between the 1970 and 2000 coding periods and include all of the years in a single estimation.

Table 2.11: Wage Regressions with Skill Levels

	All		Men		Women	
	Skills Only	Full Model	Skills Only	Full Model	Skills Only	Full Model
Skill Levels						
Cognitive	0.092**	0.058**	0.075**	0.044**	0.109**	0.071**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Interpersonal	−0.028**	−0.032**	−0.011**	−0.021**	−0.049**	−0.048**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Motor	−0.009**	−0.011**	0.005**	−0.002	−0.021**	−0.014**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Strength	0.079**	0.104**	−0.057**	−0.041**	0.168**	0.188**
	(0.010)	(0.009)	(0.016)	(0.014)	(0.014)	(0.012)
Observations	82,147	82,147	46,942	46,942	35,205	35,205
R^2	0.205	0.430	0.168	0.407	0.213	0.442

Standard errors in parentheses

Note 1: Linear regression. Dependent variable: log hourly wage in cents.

Note 2: Columns "Full Model" include age, AQFT, tenure, experience, industry, gender, and race, while columns "Skills Only" include gender.

* $p < 0.05$, ** $p < 0.01$

women than men. Skill requirement levels alone can explain 21% of variation in wages, while the model with demographic characteristics, human capital characteristics, and skills explains 43% of variation.

The conclusions from this regression are twofold: first, the skill requirements of the job are useful predictors of workers' wages; and second, the impact of skill requirements vary by gender. The latter result motivates the subsequent analysis being performed independently for men and women.

2.5 Results

This section presents the main estimation results. I discuss both the effects of skills on the probability that a worker receives a promotion, and whether skill requirement levels affect the type of promotion a worker receives.

The goal of this chapter is to examine the determinants of promotion, in particular the effects of job characteristics as measured by occupational skill requirements. I explore this question by estimating a probit model, and I take advantage of the panel nature of the NLSY79 by estimating a random effects model.[26] Each observation represents a worker staying at a firm for two consecutive survey periods, and the dependent variable is whether or not a worker received a promotion between the first and second survey years.

I include several controls for demographic characteristics, including age, race and gender. Human capital is controlled for with tenure, experience, a dummy for high-school versus college graduate, and AFQT quintiles.[27] Under job characteristics, I include the log wage level, firm size, overtime hours,[28] and union status. Year dummies are also added.[29]

Lastly, I include controls for workers' occupational skill requirement levels (cognitive, interpersonal, motor and strength). Two separate models are used, one that includes the skill measures and one that does not, and both of these models are estimated for men, women, and the entire sample combined, separately for the annual and biannual survey periods.

For ease of exposition, the random effects probit results for demographic

[26]The pooled model results are available upon request. As with Cobb-Clark (2001), the likelihood ratio test rejects the hypothesis that no individual effects are present; results discussed are, therefore, based on the random effects model.

[27]Revised 1989 AFQT scores used.

[28]Tournament theory predicts that effort exerted is positively related to probability of promotion, thus overtime hours is included.

[29]Industry controls have negligible effects on promotion probability, thus are excluded from the estimation.

and human capital variables for annual and biannual periods are presented in Tables 2.12 and 2.13, while skill level coefficients for the two periods are presented in Table 2.14.[30] Marginal effects at the population average are reported.[31] As the gap between periods differs for the annual versus biannual samples, I refrain from quantitative comparisons in the results between these groups, and focus instead on qualitative differences.

I find that women have a 3.2% lower probability of receiving a promotion in a given year during the annual period than men when skills are omitted. However, in the biannual period, the gender gap disappears entirely. Also, while Pergamit (1999) finds that blacks have a lower probability of promotion, I find little effect of race on promotion receipt in the annual period.[32] In the biannual period, however, both black and Hispanic men have a higher probability of promotion, 1.6% and 2.8% respectively. For women, race continues to have no effect in the two year period.

I find positive effects of AFQT scores on promotion probability for men in both periods, while only one quintile of scores shows significance in each period for women when skills are included. Previous studies have shown little effect of these scores on promotion, perhaps due to their linear specification.[33] Conditional on being outside of the bottom quintile, AFQT scores in the annual

[30]Job characteristics are presented in Appendix Tables A-9 and A-10.

[31]Changes in probability are evaluated at the sample means. Continuous approximation is used for discrete variables.

[32]Pergamit (1999) consider only one year, 1990, in their estimation, which might account for this discrepancy.

[33]If AFQT scores are included linearly in my model, they similarly have no impact on promotion for either men or women in the annual period.

Table 2.12: Promotion Determinants: Marginal Effects of Random Effects Probit, Demographic and Human Capital Variables, Annual Period (1988-1990)

	All		Men		Women	
	No Skills	Skills	No Skills	Skills	No Skills	Skills
Demographic						
Female	−0.032**	−0.051**				
	(0.009)	(0.010)				
Age: <25	0.046**	0.043**	0.038**	0.037**	0.055**	0.047**
	(0.009)	(0.009)	(0.013)	(0.013)	(0.014)	(0.014)
Black	0.004	0.005	0.017	0.019	−0.012	−0.010
	(0.012)	(0.012)	(0.016)	(0.015)	(0.017)	(0.017)
Hispanic	−0.000	−0.005	−0.010	−0.013	0.012	0.004
	(0.012)	(0.012)	(0.016)	(0.016)	(0.019)	(0.019)
Human Capital						
Tenure	−0.012**	−0.013**	−0.011	−0.012*	−0.013	−0.013
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Tenure^2/100	0.036	0.044	0.041	0.050	0.028	0.032
	(0.047)	(0.046)	(0.060)	(0.059)	(0.075)	(0.075)
Experience	0.017	0.016	0.029*	0.031*	0.004	−0.001
	(0.011)	(0.010)	(0.015)	(0.015)	(0.015)	(0.015)
Experience^2/100	−0.117	−0.109	−0.204*	−0.211*	−0.020	−0.001
	(0.074)	(0.074)	(0.103)	(0.102)	(0.108)	(0.107)
AFQT 2	0.036*	0.029	0.040*	0.036	0.036	0.024
	(0.015)	(0.015)	(0.019)	(0.019)	(0.025)	(0.025)
AFQT 3	0.064**	0.049**	0.056**	0.045*	0.076**	0.054*
	(0.016)	(0.016)	(0.020)	(0.020)	(0.026)	(0.025)
AFQT 4	0.051**	0.030	0.054*	0.036	0.050	0.024
	(0.017)	(0.017)	(0.021)	(0.021)	(0.027)	(0.027)
AFQT 5	0.062**	0.029	0.056*	0.024	0.070*	0.039
	(0.018)	(0.018)	(0.024)	(0.024)	(0.029)	(0.029)
High School	−0.048**	−0.029**	−0.057**	−0.036**	−0.039**	−0.028
	(0.010)	(0.010)	(0.014)	(0.014)	(0.015)	(0.015)
Observations	13,992	13,992	8,183	8,183	5,809	5,809

Standard errors in parentheses

Note 1: Dependent variable: promotion receipt between interviews; Time period: 1988-1990; Interviews annual

Note 2: Average marginal effects reported; derivatives w.r.t. entire varlist and continuous approximations of discrete variables

Note 3: Job variables and year dummies included in estimation but not displayed

Note 4: Columns labelled skills include skill requirement levels in estimation

* $p < 0.05$, ** $p < 0.01$

period have little additional effect. This is demonstrated by the coefficient for the third to fifth quintiles of AFQT scores being nearly the same. In the biannual period, the positive impact of AFQT scores increases with quintile, with a marked increase in probability for individuals in the top quintile. This result implies that a learning process may be occurring where, over a worker's career, a firm is better able to observe intelligence, leading to an increased benefit of

Table 2.13: Promotion Determinants: Marginal Effects of Random Effects Probit, Demographic and Human Capital Variables, Biannual Period (1996-2008)

	All		Men		Women	
	No Skills	Skills	No Skills	Skills	No Skills	Skills
Demographic						
Female	0.007	−0.007				
	(0.005)	(0.005)				
Age: 36-45	−0.005	−0.003	−0.002	−0.002	−0.010	−0.007
	(0.006)	(0.006)	(0.008)	(0.008)	(0.010)	(0.010)
Age: 46-55	−0.020	−0.017	−0.022	−0.021	−0.021	−0.015
	(0.012)	(0.012)	(0.016)	(0.016)	(0.019)	(0.019)
Black	0.010	0.011	0.016*	0.017*	0.003	0.005
	(0.006)	(0.006)	(0.008)	(0.008)	(0.010)	(0.010)
Hispanic	0.022**	0.021**	0.029**	0.029**	0.013	0.010
	(0.006)	(0.006)	(0.008)	(0.008)	(0.010)	(0.010)
Human Capital						
Tenure	−0.004**	−0.004**	−0.004*	−0.004*	−0.004*	−0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$\text{Tenure}^2/100$	0.007	0.007	0.007	0.007	0.008	0.008
	(0.005)	(0.005)	(0.007)	(0.007)	(0.009)	(0.009)
Experience	0.001	0.002	−0.002	−0.002	0.005	0.004
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
$\text{Experience}^2/100$	−0.007	−0.008	0.002	0.003	−0.013	−0.012
	(0.012)	(0.012)	(0.016)	(0.016)	(0.018)	(0.018)
AFQT 2	0.024**	0.018*	0.019	0.016	0.025	0.016
	(0.008)	(0.008)	(0.010)	(0.010)	(0.013)	(0.013)
AFQT 3	0.034**	0.026**	0.035**	0.030**	0.027	0.013
	(0.009)	(0.009)	(0.011)	(0.011)	(0.014)	(0.014)
AFQT 4	0.037**	0.026**	0.037**	0.028*	0.030*	0.017
	(0.009)	(0.009)	(0.012)	(0.012)	(0.015)	(0.015)
AFQT 5	0.068**	0.050**	0.072**	0.056**	0.052**	0.035*
	(0.010)	(0.010)	(0.013)	(0.013)	(0.017)	(0.017)
High School	−0.025**	−0.016**	−0.032**	−0.021**	−0.016	−0.010
	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Observations	25,554	25,554	14,537	14,537	11,017	11,017

Standard errors in parentheses

Note 1: Dependent variable: promotion receipt between interviews; Time period: 1996-2008; Interviews biannual

Note 2: 1970 Codes: 1996-2000; 2000 Codes: 2002-2008

Note 3: Average marginal effects reported; derivatives w.r.t. entire varlist and continuous approximations of discrete variables

Note 4: Job variables and year dummies included in estimation but not displayed

Note 5: Columns labelled skills include skill requirement levels in estimation

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$

higher AFQT scores in the biannual period than the annual period.[34]

Extending the sample also allows for greater age effects to be considered.[35]

[34] This observation mirrors the increase in the importance of AFQT scores on wages over a worker's career. In the NLSY79, AFQT quintile explains little wage variation in 1979, but the fraction steadily increases over the years, rising to 17% in 2008.

[35] Neither Cobb-Clark (2001) nor Pergamit (1999) control for age.

In the annual period, I find that workers under 25 years have a 3.7% higher probability of promotion per year than those in the 26-35 age range - the only other age group in that sample. In the biannual period, the age coefficients are not sufficiently significant to conclude that any real age effect is present.

I turn now to the main findings of this chapter, the effects of skill requirement levels on promotions. These results are divided into the effects of the skill levels themselves and the effects of including skills on other variables, which can be determined by comparing the non-skill and skill columns. The most significant and consistent finding in the former group is the importance of cognitive skill requirements on promotion probability. For both men and women, in both sample periods, higher levels of cognitive skills are associated with large increases in promotion probability. In the annual period, a one-unit increase in this skill requirement results in a 1.7% increase in the probability of promotion in a given year - or, put differently, a one standard deviation increase in cognitive skill requirement yields a 4.1% higher probability of promotion each year. This gap is similar in size to the difference between a Financial Manager and a Building Manager from the example considered above.

Interpersonal skill requirement, though it has a highly positive correlation with cognitive skills, has a negative impact on promotion receipt in the annual period for women. This negative effect is on the same scale as the positive effect of cognitive skills, with a one standard deviation change in interpersonal skill requirement level reducing promotion probability by 4.1% for women in

Table 2.14: Promotion Determinants: Marginal Effects of Random Effects Probit, Skill Levels, Annual and Biannual Periods

	Annual			Biannual		
	All	Men	Women	All	Men	Women
1970 Codes						
Cognitive	0.016**	0.015**	0.016**	0.012**	0.013**	0.012**
	(0.003)	(0.005)	(0.005)	(0.002)	(0.003)	(0.003)
Interpersonal	−0.012*	−0.004	−0.017*	−0.019**	−0.021**	−0.016**
	(0.006)	(0.008)	(0.008)	(0.004)	(0.005)	(0.005)
Motor	−0.004	−0.000	−0.010*	−0.009**	−0.011**	−0.009**
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
Strength	−0.088**	−0.043	−0.173**	−0.067**	−0.030	−0.115**
	(0.030)	(0.047)	(0.045)	(0.019)	(0.030)	(0.031)
2000 Codes						
Cognitive				0.007**	0.006	0.010*
				(0.002)	(0.003)	(0.004)
Interpersonal				−0.001	0.004	−0.006
				(0.004)	(0.005)	(0.006)
Motor				−0.004	−0.000	−0.010*
				(0.002)	(0.003)	(0.004)
Strength				−0.047	−0.044	−0.042
				(0.024)	(0.038)	(0.036)
Observations	13,992	8,183	5,809	25,554	14,537	11,017

Standard errors in parentheses

Note 1: Dependent variable: promotion receipt between interviews

Note 2: 1970 Codes: 1996-2000; 2000 Codes: 2002-2008; Annual: 1988-1990; Biannual: 1996-2008

Note 3: Average marginal effects reported; derivatives w.r.t. entire varlist and continuous approximations of discrete variables

Note 4: Job, human capital and demographic variables and year dummies included in estimation but not displayed

* $p < 0.05$, ** $p < 0.01$

the annual period. In the biannual period, during the 1970 Census coding period of 1996-2000, interpersonal skill levels have a negative effect for both men and women. However, under the 2000 Census occupation coding scheme, a large change occurs: cognitive skills decline in importance, though still remain positive and significant, while interpersonal skills become insignificant for both men and women.

Motor skill levels are either negatively or insignificantly related to promotion. For example, a one standard deviation increase in the level of motor skills for men in the biannual, 1970 occupation coding period would result in a 1.5%

decline in promotion probability.[36] The effects of motor skills differ between the 1970 and 2000 coding schemes, though not as substantially as for cognitive and interpersonal skills. Overall, the level of strength skill required has a negative effect on promotion in both periods and under both coding schemes, but is only statistically significant for women. A one standard deviation increase in strength requirement in the 2000 coding period would lead to a 1.0% reduction in the probability of promotion. Though motor and strength skill requirement levels do impact promotion probability, their effects are overshadowed by the importance of cognitive skills and, to a lesser extent, interpersonal skills.

Thus, it appears that, though the skill distributions looks similar between the 1970 and 2000 Census coding schemes, an important change has nonetheless taken place. The importance of cognitive skill requirement declines, while interpersonal skill requirement become less negatively related to promotion. Motor and strength skill requirements also diminish somewhat in importance.

As I noted previously, I find that during the annual period, there is a negative gender effect. Without skills, women in the annual period have a 3.2% lower probability of promotion per year, while in the estimation with skills they have a 5.1% lower probability of promotion per year. This is likely due to women's jobs having, on average, higher levels of cognitive skill requirements, which, as has been discussed, are positively related to promotion. Failure to include proper occupation measures - in this case skill requirement levels -

[36]This is a reduction in the probability of the worker reporting at least one promotion since the previous interview, which for most workers is a two-year period.

would lead to an underestimate of the gender gap in promotion receipt. While women and men have similar observed promotion rates, controlling for other demographic, human capital, and job characteristics, women appear to have a significantly lower probability of promotion than men earlier in their careers, and the similarity in their rates of promotion is partly due to their selection towards higher cognitive jobs.

Another notable effect resulting from the inclusion of skill levels is the importance of AFQT scores. Without skills, AFQT scores are statistically significant predictors of promotion for both men and women in both time periods. Including skills leads to a reduction in the importance and significance of these scores as predictors. For women, the effect is more drastic: including skills nearly eliminates the relationship between AFQT scores and promotion. While a move to a higher AFQT quintile increases the probability of promotion receipt for women, especially in the second period, this appears to be largely driven by the skill requirement levels within each AFQT grouping; workers in the lowest AFQT quintile are in jobs with a mean cognitive skill requirement level of 6.9, while for the highest quintile the level is 10.4.[37] For men, though the significance and size of the AFQT coefficients are reduced when skill requirement levels are added, they nonetheless remain statistically significant overall, especially in the biannual period.

Being a high school graduate as opposed to a college graduate leads to a

[37] See Table A-7.

reduction in the probability of promotion for men and women in both time periods. This educational gap is, however, greatly reduced in all estimations when occupational skill requirements are added. For example, the high school variable for men in the annual time period changes from -5.6% to -3.6% when skills are included - a 36% reduction. Similar to the drop in AFQT scores, this drop is largely due to the difference in skill requirement levels between these educational groups, especially the higher cognitive levels for college graduates.[38] This result, as well as the decline in AFQT importance with skill inclusion, demonstrates one of the main findings of this chapter: although measures for ability and education are relevant to promotion receipt in and of themselves, it is important to control for the type of job that a worker is in, measured here using skill requirement levels. Including skill requirements reduces the effects of education and ability, as measured by AFQT scores, on promotion. Thus, part of the impacts of education and ability on promotion derives from their effects on job assignment, while a still important fraction seems to affect promotion receipt directly.

While I have shown that skill requirement does significantly impact the likelihood that a worker receives a promotion, it may be the case that the wage gains from promotion differ by skill requirement as well. Booth, Francesconi, and Frank (2003), for example, finds that the wage growth from promotion is lower for women than men, indicating that the *type* of promotion, in addition to

[38] See Table A-8 for skill requirement levels by educational group.

Table 2.15: Wage Change from Promotion

	All	Men	Women
Cognitive	−0.002	−0.002	−0.002
	(0.002)	(0.003)	(0.003)
Interpersonal	−0.006	0.001	−0.013*
	(0.004)	(0.005)	(0.005)
Motor	−0.006**	−0.004	−0.008**
	(0.002)	(0.003)	(0.003)
Strength	−0.018	0.010	−0.035
	(0.020)	(0.032)	(0.031)
Observations	6,664	3,857	2,807

Standard errors in parentheses
Note 1: Dependent variable in log wage change.
Note 2: All specifications control for age, tenure, experience, race, year, and industry.
* $p < 0.05$, ** $p < 0.01$

the probability of promotion, matters to worker careers. I examine this question by running a regression of wage change on skill requirements, controlling for job and demographic characteristics, conditional on the worker receiving a promotion.

Results from this regression are shown in Table 2.15.[39] The only skill variable that is statistically significant is the motor skill, which has a negative sign. A one standard deviation increase in motor skill requirement results in an approximately 1% lower wage gain upon promotion. Since the motor skill showed either no effect or a negative effect on promotion probability, this result strengthens the impact of skill requirement on career outcome through promotion: high motor skill workers are both less likely to receive a promotion (for some groups), and receive lower wage gains in expectation upon promotion. Otherwise, I conclude that while skill requirement impacts the probability that

[39]Separate results for the annual and biannual periods are available in Appendix Tables A-11 and A-12.

a worker receives a promotion, it does not significantly affect the outcome conditional on a promotion being received.

2.6 Conclusion

NLSY79 and DOT data are combined to study the determinants of promotion while controlling for job characteristics more completely than previous studies by incorporating occupational skill requirements. Also, a longer timeframe than in previous work on promotions in the NLSY79 is used, which allows for greater life-cycle effects to be considered. Non-skill related findings include: a gender gap in earlier periods, which disappears in later years; a positive race gap for black and Hispanic men in the later period, while race has no effect in the earlier period and no effect in the female group; and a positive effect of AFQT scores on promotion, especially for men, with some evidence of firm learning occurring over the worker's career.

Occupational skill requirement levels are found to have significant impacts on a worker's probability of promotion. Especially important is the positive impact of cognitive skill levels on promotion; interpersonal skills have an important, though overall lesser, negative effect. Furthermore, the inclusion of skill measures in the estimation affects other variables, often substantially, both in significance and magnitude: the gender gap is widened, and both AFQT scores as well as the effect of education decline in importance when skills are added to the estimation.

These results highlight the importance of controlling for a worker's occupation more rigorously than previous work has done. It furthers recent work, notably Ingram and Neumann (2006) and Poletaev and Robinson (2008), both of which demonstrate the relevance and applicability of the DOT occupational skill requirement measures. The Gibbons and Waldman (1999) model, which is the standard in the internal labor market literature regarding promotions, includes only a single measure of worker ability. I demonstrate here that multiple skill requirement measures affect promotion receipt.

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Chapter 3

Skills, Tasks, and Occupational Choice

3.1 Introduction

A worker's hierarchical level has been shown to have a significant effect on wages.[1] While there is a large literature that investigates the importance of levels, there has been little work that examines what effect including levels has on a model of occupational mobility. In this chapter, I present evidence suggesting that not only does hierarchical level affect workers' wages, it also impacts: (1) the probability that a worker changes occupations; (2) their wage losses during unemployment; and (3) the tasks that they perform on the job. I estimate a structural occupational choice model with hierarchical level mobility and skill accumulation in order to match these empirical observations, and to quantify the sources of wage growth over the life cycle.

[1] Baker, Gibbs, and Holmström (1994), among others.

The importance of levels has been confirmed in numerous studies of both single-firm and, to a lesser extent, multi-firm data. The seminal contribution to this literature is Baker, Gibbs, and Holmström (1994), who show that wages are closely tied to job level and changes in job level significantly affect wages. Subsequent studies by Dohmen, Kriechel, and Pfann (2004), Kauhanen and Napari (2012), and da Silva and van der Klauuw (2011) all demonstrate the important of hierarchical level to wages. In this chapter, I confirm these findings by showing that hierarchical level has a significant impact on worker's wages even in a large-scale, nationally-representative data set, the German Socio-Economic Panel (GSOEP). In addition to greatly impacting wages, I show that a worker in the lowest hierarchical level has a significantly higher probability of undergoing an occupation change than other workers. Furthermore, workers who return to a lower level within an occupation after an unemployment spell suffer higher wage losses than those who return to the same or a higher level. This result holds even when controlling for worker characteristics and for occupation at a highly disaggregated level. What these results demonstrate is that a worker's position within an occupation can greatly impact their labor market outcomes beyond their wage levels alone.

A primary focus of this chapter is investigating the effects of hierarchical levels on the specificity of human capital. The nature and specificity of human capital is an important topic in labor economics. Recent work by Kambourov and Manovskii (2009) points to human capital being largely specific to the occupation, while Pavan (2011) argues that firm-specific matches play an important role in wages. Gibbons and Waldman (2004) propose the idea that a job consists of a set of tasks performed by the worker, and that workers accumulate task-specific human capital which is transferable between jobs. There has been significant interest in this idea recently. Poletaev and Robinson (2008) show that displaced workers' wage losses are larger for those who move to "farther" occupations, in terms of tasks performed, than those who move to "closer" occupations. Similarly, Gathmann and Schönberg (2010) find that a worker's pre- and post-occupation-change wages are more closely related when the worker moves between occupations with similar task usages.[2] Both of these studies point to the importance of task-specific human capital.

In Yamaguchi (2010, 2012) and Sanders (2012), occupations are defined by the tasks that they utilize. Thus, two occupations that are identical in terms of task usage are equivalent. While this approach greatly reduces the computations burden and allows for hundreds of occupations to be included, it does not allow for human capital to be specific to an occupation. In this chapter, I allow for human capital to be both specific to tasks (and thus transferable between jobs) and specific to an occupation (and thus not transferable outside of the occupation).

[2]See also Spitz-Oener (2006), Black and Spitz-Oener (2007), Bacolod and Blum (2008), Autor and Handel (2013) and Acemoglu and Autor (2011) for other papers that investigate tasks.

Thus far, the task usage literature has mostly relied on a worker's occupation to infer their task usage since such information is rarely available in panel data sets. Task usage is typically assigned to workers by taking the mean task usage by occupation in another data set, such as the Dictionary of Occupational Titles (DOT) or the German Qualification and Career Survey (GQCS), and imposing that value on all workers in a given occupation in the panel data set. Autor and Handel (2013), however, demonstrate that while occupations can explain a large amount of task usage variation, significant variation within occupations remains. Since the GQCS includes a worker's hierarchical level, I am able to assign task usage by both occupation and level within occupation. As a result, not only am I able to perform a more accurate task assignment by using more information than the worker's occupation alone, the process allows for the variation in task usage within occupation that Autor and Handel (2013), as well as this chapter, demonstrate exists to a large degree. I show that cognitive task usage typically increases, and manual task usage typically decreases, moving up in levels. As task usage varies within an occupation across levels, it is a natural step to incorporate hierarchical mobility into a model that seeks to quantify the relative importance of task-specific human capital to wage growth.

I estimate a structural occupational choice model with hierarchical levels to try and match the observed relationships between level, occupation change and wage losses during unemployment, and to quantify the specificity of human capital. I also estimate a version of the model without levels, and I compare the results to determine if the inclusion of levels affects the quantification of human capital specificity. In my model, each occupation-level contains a set of tasks that the worker performs. Workers can move within-occupation across hierarchical levels (i.e. through promotions and demotions), and tasks performed vary both by occupation and by level within an occupation. My model can be interpreted as a generalization of the Gibbons and Waldman (1999) framework with multidimensional abilities.[3] Workers also face search frictions and a probability of job destruction, and can only change their occupation-level if they receive a job offer.

I estimate this model using labor market histories from the GSOEP and by assigning task usages using the GQCS. The model is estimated using indirect inference. I am able to match the wage profiles (both overall and for each occupation) and the allocation of workers across occupations over the life cycle. I am also able to match the empirical observations that lower-level workers are more likely to undergo an occupation change, and that demotions during unemployment lead to significantly higher wage losses than if the worker returned to the same or a higher level.

I run counterfactual simulations to separately assess the importance of task-specific versus occupation-specific human capital. Shutting down task-specific human capital accumulation reduces the overall mean wage level by

[3]See also Brilon (2010), DeVaro, Ghosh and Zoghi (2012), and DeVaro and Gürtler (2012) for models where multidimensional skills are incorporated with promotion.

32.7% while eliminating occupation-specific human capital accumulation results in a 17.6% reduction. These effects vary greatly by occupation, with occupation-specific skill growth dominating in the blue-collar occupation, while task-specific skill growth dominates in the white-collar occupation.[4] Incorporating hierarchical levels significantly affects the estimated relative importance of these sources of human capital accumulation. I find that a model that omits levels significantly underestimates the importance of occupation-specific human capital to workers in the blue-collar occupation, while underestimating the importance of task-specific human capital to workers in the white-collar occupation.

This chapter is organized as follows. Section 3.2 describes the data used in the analysis, discusses the hierarchical level assignment procedure, and motivates the inclusion of hierarchical levels in a model of occupational mobility. Section 3.3 describes the model. Section 3.4 describes the occupational aggregation method, estimation technique, and identification. Section 3.5 discusses the parameter results, model fit, and counterfactual simulation results. Section 3.6 concludes.

[4]The result that skills are more occupation-specific for the blue-collar occupations is mirrored by Keane and Wolpin (1997), who find that blue-collar experience is more valuable than white-collar experience, controlling for overall experience.

3.2 Data

Two sources of data are needed to estimate the model. The first provides the labor market histories of workers. The second assigns task usage vectors to each occupation-level. Labor market histories are taken from the German Socio-Economic Panel (GSOEP), while task usage data are derived from the German Qualification and Career Survey (GQCS). Previous papers have primarily used the National Longitudinal Survey of Youth (NLSY) to estimate occupation-choice models. Instead, I use these German data sets since they both include a variable, comparable between the two, which can be interpreted as a worker's hierarchical position.

3.2.1 German Socio-Economic Panel

The GSOEP is a yearly, representative, longitudinal survey of German households, which consists of both a household survey and an individual survey of all household members over age 16. The initial survey began in 1984, and there have have been a total of seven additional waves, including an East German sample added in 1991 during reunification. This analysis uses data from 1984 to 2009.

The primary motive for using this data set over others is the inclusion of an occupational position question, which I interpret as a worker's hierarchical position, that I use to assign workers to one of three hierarchical levels. As this question is independent of the worker's recorded occupation, I am able to assign worker position without relying on occupational coding, which can mask true hierarchical mobility.[5] For example, in the NLSY, only roughly 40% of promotions correspond to a change in three-digit occupation code.[6] I discuss this variable and the level assignment procedure in more detail in Section 3.2.3.

My estimation sample is based on men between ages 18 and 60.[7] I drop the East German population, since reunification occurs during my sample period. To avoid issues associated with some workers entering the labor market later, I select only workers with fewer than 13 years of education. Due to the features of the German educational system, selecting based on years of education has the effect of choosing workers from a number of different educational categories. However, it allows me to be confident that the worker has entered the labor market by age 18, while still providing as large a sample size as possible. I include observations where the worker is in the labour market, either unemployed or employed. I drop workers in the agricultural sector and military, as well as workers with missing education information. Also, I clean the data by dropping observations where net monthly income is less than 400 Euro/month.[8] I consider only full-time workers, defined as those working over

[5]A worker's level does not depend explicitly on their occupation, though the distribution of workers across levels does vary across occupations.

[6]See Cassidy (2012).

[7]While the official retirement age in Germany is 65, the effective age as estimated by the OECD is several years earlier.

[8]All wage figures are in 2009 Euros.

Table 3.1: Summary Statistics, Estimation Sample

	All Mean/s.d.	Lower Level Mean/s.d.	Middle Level Mean/s.d.	Upper Level Mean/s.d.
Age	40.76	40.58	40.01	43.60
	(10.21)	(10.56)	(10.26)	(8.75)
Tenure	12.77	10.83	12.92	16.29
	(9.86)	(8.86)	(9.91)	(10.64)
Experience	20.00	19.86	19.27	22.69
	(10.63)	(11.03)	(10.61)	(9.36)
Net Income	1,903.23	1,651.75	1,869.35	2,538.90
	(659.12)	(444.43)	(524.93)	(955.45)
Blue-Collar	0.67	0.85	0.64	0.41
	(0.47)	(0.36)	(0.48)	(0.49)
White-Collar	0.33	0.15	0.36	0.59
	(0.47)	(0.36)	(0.48)	(0.49)
Lower Level	0.33			
	(0.47)			
Middle Level	0.52			
	(0.50)			
Upper Level	0.16			
	(0.36)			
Observations	45,322	14,787	23,430	7,099

Income in net monthly wages, 2009 Euros. All time variables measured in years. Source: German Socio-Economic Panel, 1984-2009.

30 hours per week. Only workers in Blue-Collar, White-Collar and Civil Service jobs are used.[9] I allocate Civil Service workers to the White-Collar group. Lastly, I require that the worker is observed for at least five years in the labor market. In total, I am left with a sample of 4550 workers, and a total of 50,578 worker-years of observations, which results in an average of roughly 14 years per worker.

Table 3.1 presents summary statistics of the sample. To illustrate the relationships between levels and other variables, I show descriptive statistics for levels 1, 2, and 3 in columns two, three, and four, respectively. Several obvious patterns emerge. Age, tenure, and experience all rise with level, though age does not increase as greatly as experience and tenure. As expected, there is

[9]The means dropping self-employed and workers and trainees.

a strong positive relationship between level and income. I discuss the occupational aggregation in Section 3.4.2.

3.2.2 German Qualification and Career Survey

The German Qualification and Career Survey is a cross-sectional worker survey with five waves: 1979, 1986, 1992, 1998 and 2006. Questions asked cover worker qualification and working conditions, as well as a limited number of worker characteristics. While the number of workers varies by survey, it ranges from 20,000 to 30,000 per wave.[10]

For each survey, workers are asked a series of yes/no questions concerning their task usage in their job. For example, a worker might be asked whether or not they do any cleaning. While each survey asks questions of this nature, their wording and number vary between the waves. As a result, direct comparison across all of the cross-sections is problematic. Instead, I focus on the 1986 and 1992 waves as these surveys are, in terms of task questions, nearly identical. I use only men to assign tasks, since my labor market data include only men. After cleaning the data, I am left with 31,516 observations.

In total, I use 20 task-related questions in my analysis.[11] The first group of tasks are denoted as cognitive and include: research, planning, law, calculate,

[10] See Gathmann and Schönberg (2010), who also use these data to assign task usages.

[11] Gathmann and Schönberg (2010) group tasks into Analytical, Interactive, and Manual. I use the same grouping, except I combine the Analytical and Interactive into the Cognitive group.

IT, write, educate, publish, guide, and buy. The second task group, manual, includes: maintain, secure, repair, grow, create, build, entertain, clean, and pack. A worker is said to perform the cognitive task if they perform any of the tasks in the cognitive group, and similarly for manual. For example, if a worker responds “yes” to the cleaning task, then their manual task variable is one. Additional “yes” responses to tasks in the manual group have no effect, as the manual task usage is already set to one. If the worker does not respond “yes” to any of the tasks in one of the two groups, then that task usage group is set to zero. Table 3.3 demonstrates the grouping of these variables, as well as their descriptive statistics for only men. Column (1) shows results for the entire sample, while column (2) shows blue-collar workers and column (3) white-collar workers. There is a strong negative correlation of -0.521 between cognitive and manual tasks.

Previous works which examine task usage, such as Ingram and Neumann (2006), Poletaev and Robinson (2008), Yamaguchi (2010, 2012), and Sanders (2012), make use of the Dictionary of Occupational Titles (DOT), or its successor O*NET, to assign task usages to occupations. However, as I want to focus on mobility within occupations across hierarchical levels, I require data which allow for task assignment by both occupation and level. The GQCS includes a question which asks for a worker’s occupational position, and is nearly identical to the occupational position question in the GSOEP. This allows me to assign tasks by both occupation and level. Hierarchical assignment is done in

Table 3.2: Summary Statistics, Task Usage

	All Mean/s.d.	Blue-Collar Mean/s.d.	White-Collar Mean/s.d.
Cognitive	0.63	0.28	0.91
	(0.48)	(0.45)	(0.29)
Research	0.15	0.08	0.23
	(0.36)	(0.27)	(0.42)
Plan	0.13	0.06	0.18
	(0.34)	(0.24)	(0.39)
Law	0.14	0.02	0.26
	(0.35)	(0.14)	(0.44)
Calculate	0.20	0.03	0.30
	(0.40)	(0.17)	(0.46)
IT	0.13	0.02	0.24
	(0.34)	(0.15)	(0.43)
Write	0.32	0.08	0.51
	(0.47)	(0.28)	(0.50)
Educate	0.16	0.04	0.26
	(0.36)	(0.20)	(0.44)
Publish	0.06	0.00	0.11
	(0.24)	(0.06)	(0.31)
Guide	0.32	0.12	0.48
	(0.47)	(0.32)	(0.50)
Buy	0.23	0.06	0.29
	(0.42)	(0.24)	(0.46)
Manual	0.69	0.96	0.42
	(0.46)	(0.19)	(0.49)
Maintain	0.03	0.01	0.04
	(0.16)	(0.09)	(0.19)
Secure	0.06	0.04	0.08
	(0.23)	(0.20)	(0.27)
Machinery	0.30	0.48	0.14
	(0.46)	(0.50)	(0.35)
Repair	0.30	0.50	0.10
	(0.46)	(0.50)	(0.30)
Grow	0.05	0.05	0.01
	(0.21)	(0.21)	(0.11)
Create	0.08	0.14	0.03
	(0.27)	(0.35)	(0.16)
Build	0.15	0.26	0.04
	(0.35)	(0.44)	(0.20)
Entertain	0.02	0.01	0.02
	(0.14)	(0.09)	(0.14)
Clean	0.05	0.07	0.03
	(0.22)	(0.26)	(0.16)
Pack	0.26	0.31	0.18
	(0.44)	(0.46)	(0.39)
Observations	32,223	13,938	14,401

Source: German Qualification and Survey, 1986 and 1992 waves.

Table 3.3: Task Usages

	Cognitive	Manual
Blue Collar, Level 1	0.14	0.86
Blue Collar, Level 2	0.21	0.79
Blue Collar, Level 3	0.40	0.60
White Collar, Level 1	0.53	0.47
White Collar, Level 2	0.68	0.32
White Collar, Level 3	0.75	0.25

Source: German Qualification and Career Survey, 1986 and 1992 waves.

the same manner as in the GSOEP.

Task assignment follows the same procedure as Gathmann and Schönberg (2010), except I assign tasks to occupation-levels instead of occupations.[12] Each occupation-level's task usage is the probability of a worker in that occupation-level reporting using that task; in other words, it is the mean task usage within each occupation-level group. I then re-weight the task usage to sum to one. While other task usage sources such as the DOT have a measure of task usage intensity within an occupation, workers in the GQCS respond only "yes/no" to task questions. While workers are not asked how intensively they use a task, workers in jobs where a certain task is used more intensively should be more likely to report "yes" when asked about their task usage. As a result, it is likely that higher task usage represents task usage intensity to some degree. While not an ideal measure, it does allow for the assignment of task usage by level, which is not possible using data such as the DOT. Furthermore, if reporting performing one task makes a worker less likely to report performing another task, then weighting the tasks to represent fractions instead of intensity helps

[12]I used the 1998 and 2006 waves of the GQCS to produce a cross-walk between the ISCO-88 codes used in the GSOEP and the 1988 revised vocational classification.

alleviate the issues related to the lack of intensity measure.

3.2.3 Hierarchical Levels

In this section, I discuss the procedure by which I assign workers to hierarchical levels and present empirical evidence that motivates incorporating this type of mobility in the model.

The GSOEP and GQCS are unique in that they both contain a survey question that asks for a worker's rank in their job. A sample of the survey question is available in Appendix B.1. Lluis (2005) uses this feature of the GSOEP to assign workers to one of four hierarchical levels. I follow her assignment procedure but I aggregate the top two levels, leaving me with a total of three hierarchical levels.[13] This question is specific to the worker's position, i.e. their white-collar, blue-collar, or civil-servant status.[14] However, it is not specific to the worker's occupation itself. For instance, the worker is not asked what rank of plumber they occupy, but instead what their rank is as a blue-collar worker. This is an important feature of the question since it makes it feasible to aggregate occupations together and combine their hierarchical levels. To see why this is the case, consider a manual laborer and a plumber, both of who belong to the same aggregate occupational group. If the hierarchical level question

[13]Since Chapter four of this dissertation also uses the assignment procedure but has four levels, I include the four-level assignment procedure in Appendix B.1

[14]Apprentice/Trainee and self-employed divisions are also present, but I drop these workers from my sample.

were specific to the worker's occupation, then a manual laborer who is high-skilled compared to other laborers might report being in the high hierarchical level within that occupation, even if that worker is, overall, lower skilled than most plumbers. Aggregating the plumber and manual laborer occupations together would therefore result in lower-skilled manual laborers being assigned to higher hierarchical levels than higher-skilled plumbers. But if the hierarchical level question were not specific to the occupation, then even a relatively high-skilled manual laborer is likely to report being in the lower hierarchical level, and as a result when the plumber and manual laborer occupations are aggregated, there is less chance of improper hierarchical level assignment.

A potential issue with assigning workers to hierarchical levels is that they might simply be replicating the information contained in the occupation code, in that workers in high-skilled occupations report being in a higher level, while workers in low-skilled occupations report being in a lower level. Due to the wording of the level question, we can expect that occupations vary in terms of the distribution of workers across levels, with some occupations weighted towards lower levels and some towards higher levels. This is indeed the case: using the GSOEP estimation sample, I find that 155 of the 265 reported occupations have fewer than 5% of workers in that occupation in one of the three levels. However, these occupations contain only an average of 102 workers while the overall average per occupation is 298, so the low representation is likely due at least in part to a lack of observations. Also, 67% of workers are employed in occupations where there are at least 5% of workers employed at all levels of the occupation. So while the distribution of workers across levels within an occupation does vary across occupations, most workers are employed in an occupation with a non-trivial representation of workers at each level. This provides evidence that the worker's reported level does not simply duplicate the information contained in the occupation code, even though occupation does impact the distribution of workers across levels.

Since the worker's hierarchical level is self-reported, there is the potential for spurious level changes to occur. To help mitigate this problem, I clean the data using a procedure similar to that used by Yamaguchi (2010), who assumes that occupation changes within a firm are misspecified (and thus are corrected) if the worker eventually returns to the previous occupation while at the same firm. I clean hierarchical level cycles in a similar manner: if a worker changes levels between period-1 and period-2, but returns to the period-1 level in period-3, the worker's level in period-2 is set to the period-1(and period-3) level. This procedure assumes that such level cycles are miscodings. The promotion rate is reduced from 10.7% to 4.8% as a result of this procedure.[15]

There is strong support in the literature for the importance of hierarchical level to worker career outcomes. Notably, Baker, Gibbs, and Holmström (1994) demonstrate the importance of job level to worker wages using a single-firm

[15]While this procedure likely mislabels some genuine promotions, the wage change from promotion rises from 2.6% to 3.6%. Furthermore, promotions that were corrected to be non-promotions as a result of this procedure have an average wage change of only 1.9%. These results indicate that many of the corrected "promotions" were, in fact, spurious.

U.S. data set. Dohmen, Kriechel, and Pfann (2004) also confirm the strong link between job level and wage using personnel data from the Dutch aircraft manufacturer Fokker. Using nationally-representative Finnish data, Kauhanen and Napari (2012) also demonstrate the importance of job level to wages, and note that job level can explain a substantial fraction of wage variation.

I replicate these analyses using the GSOEP to investigate the connection between hierarchical level and worker wages. This is done by estimating a set of wage regressions, controlling for demographic characteristics, human capital variables, and hierarchical levels. Table 3.4 shows the results. Column (2) shows the importance of hierarchical level to log wage level, even in the presence of other controls: workers in the second level have 15% higher wages than workers in level 1, while those in level 3 have 32.8% higher wages. Column (5) repeats this estimation but using a fixed-effect model. While the effect of level is diminished to some extent, the results clearly show that workers in higher levels have higher wages overall. These results mirror those found in the studies cited above, and confirm the importance of hierarchical position to worker wages.

Not only do hierarchical levels themselves affect wages, but changes in hierarchical levels are associated with large changes in wages. While the GSOEP does not contain data on promotions and demotions directly, I say that a worker has been promoted if they report being in a higher level this year than in the previous year, and analogously for a demotion. One of the consistent findings

Table 3.4: Wages and Hierarchical Level

	OLS			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.033**	0.033**		0.002	0.003	
	(0.004)	(0.004)		(0.007)	(0.007)	
Experience^2	−0.088**	−0.094**		−0.097**	−0.103**	
	(0.019)	(0.019)		(0.024)	(0.024)	
Experience^3/1000	0.007*	0.009**		0.010**	0.011**	
	(0.003)	(0.003)		(0.004)	(0.004)	
Tenure	0.025**	0.023**		0.017**	0.015**	
	(0.002)	(0.002)		(0.002)	(0.002)	
Tenure^2/100	−0.120**	−0.110**		−0.090**	−0.086**	
	(0.011)	(0.011)		(0.012)	(0.012)	
Tenure^3/1000	0.019**	0.017**		0.015**	0.014**	
	(0.002)	(0.002)		(0.002)	(0.002)	
Age	0.111**	0.092**		0.112**	0.101**	
	(0.016)	(0.016)		(0.019)	(0.019)	
Age^2/100	−0.278**	−0.231**		−0.173**	−0.149**	
	(0.041)	(0.040)		(0.048)	(0.048)	
Age^3/1000	0.022**	0.018**		0.012**	0.011**	
	(0.003)	(0.003)		(0.004)	(0.004)	
Middle Level		0.149**	0.189**		0.142**	0.145**
		(0.006)	(0.005)		(0.008)	(0.008)
Upper Level		0.328**	0.470**		0.190**	0.221**
		(0.009)	(0.007)		(0.011)	(0.011)
Occupation	Yes	Yes	No	Yes	Yes	No
Industry	Yes	Yes	No	Yes	Yes	No
Observations	44,553	44,553	44,553	44,553	44,553	44,553
R^2	0.177	0.204	0.095	0.077	0.086	0.046

Standard errors in parentheses. Dependent variable is log monthly wages, 2009 Euros. Time variables measured in years. All regressions include year dummy variables. Source: German Socio-Economic Panel, 1984-2009.
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$

in the internal labor market literature is that large wage increases are typical upon promotion. In the GSOEP, I find that a worker receiving a promotion experiences on average about three times the expected wage growth of a worker who is not promoted. Also, I find that workers who are demoted (move to a lower level) experience real wage declines on average. These results suggest that not only are levels themselves important to worker careers, but also that changes in levels are indicators of career progression.

A worker's hierarchical level also impacts the probability that the worker undergoes an occupational change. I demonstrate this feature of the data by estimating a linear probability model of occupation change controlling for worker characteristics, occupation, and level in the initial period. Results are shown in Table 3.5. I find that workers in the lowest level have 3-5% more occupational mobility per year than in the higher two levels, compared to an overall 17% per year occupation change rate using ISCO-88 codes. This represents approximately a 25% difference in the probability that a worker changes occupations. With the blue-collar/white-collar occupation coding used in this chapter, the story becomes more complex: while occupational mobility rates are higher for those in the lowest level overall, workers in blue-collar level 1 have the lowest occupational change rate of any occupation-level. The rate climbs by level in blue-collar, is highest for white-collar level 1, and declines with level in white-collar. This pattern can be partly explained by considering the cognitive task usage of an occupation-level. Including the worker's cognitive task usage in the previous occupation change regression strengthens the impact of being in the lower level. Overall, I find that workers in occupation-levels with high cognitive task usage are more likely to change occupations. Since lower levels typically have lower cognitive task usages, and cognitive task usage is positively related to occupation change probability, omitting this control mitigates the impact of level on occupation change to some degree. This additional control

Table 3.5: Occupation Change and Hierarchical Level

	ISCO			WC/BC		
	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.007*	0.007*	0.008**	−0.003	−0.003	−0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Experience^2	−0.032*	−0.031*	−0.032*	0.011	0.012	0.011
	(0.015)	(0.015)	(0.015)	(0.008)	(0.008)	(0.008)
Experience^3/1000	0.004	0.004	0.004	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Tenure	−0.013**	−0.013**	−0.013**	−0.002**	−0.002**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure^2/100	0.068**	0.067**	0.067**	0.014**	0.014**	0.014**
	(0.009)	(0.009)	(0.009)	(0.004)	(0.004)	(0.004)
Tenure^3/1000	−0.010**	−0.010**	−0.010**	−0.002**	−0.002**	−0.002**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Age	−0.045**	−0.045**	−0.042**	0.010	0.010	0.011
	(0.013)	(0.013)	(0.013)	(0.007)	(0.007)	(0.007)
Age^2/100	0.099**	0.100**	0.092**	−0.022	−0.022	−0.026
	(0.033)	(0.033)	(0.033)	(0.017)	(0.017)	(0.017)
Age^3/1000	−0.007**	−0.007**	−0.007*	0.001	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Lower Level	0.030**	0.050**	0.049**	0.004	0.008**	0.008**
	(0.005)	(0.006)	(0.006)	(0.002)	(0.003)	(0.003)
Cognitive		0.150**	0.155**		0.035*	0.046*
		(0.032)	(0.032)		(0.018)	(0.018)
Wage Quintiles						
Quintile 2			−0.018**			−0.005
			(0.006)			(0.003)
Quintile 3			−0.023**			−0.012**
			(0.006)			(0.003)
Quintile 4			−0.029**			−0.014**
			(0.006)			(0.003)
Quintile 5			−0.019**			−0.011**
			(0.006)			(0.003)
Observations	37,043	37,043	37,043	37,043	37,043	37,043
R^2	0.215	0.216	0.216	0.036	0.036	0.037

Standard errors in parentheses. Dependent variable is binary, and equals one if an occupation change occured, and zero otherwise. Column (1) measures occupation using ISCO-88 codes, while column (2) uses blue-collar/white-collar codes. Time variables measured in years. Wages measured in log monthly wages, 2009 Euros. All variables measured in initial period. All regressions include year, occupation and industry dummy variables. Source: German Socio-Economic Panel, 1984-2009.
* $p < 0.05$, ** $p < 0.01$

helps to explain the relationship observed in the blue-collar/white-collar division where occupational mobility increases with level in the blue-collar occupation. I find that when using the blue-collar/white-collar codes and controlling for task usage and other worker and job characteristics, workers in the lowest level experience 0.8% more occupational mobility in a given year, compared to the overall rate of 3.0%. While a lower absolute effect than observed using the

ISCO-88 codes, the relative increase is approximately the same, with workers in the lower level having approximately 27% higher probability of changing occupations.

Groes, Kircher and Manovskii (2010) find that occupational mobility exhibits a U-shaped pattern, where low and high earners within an occupation are the most likely to move. Since there is a strong connection between hierarchical level and earnings, my results may be picking up this relationship. I test this by including occupation-specific wage quintiles in the linear regression specification. The inclusion of these variables does not significantly impact the positive effect that being in the lower level has on the probability of occupational mobility. Interestingly, the wage quintile coefficients are negative and, with the exception of quintile 2 in the WC/BC estimation, statistically significant. Furthermore, they appear to exhibit the U-shaped pattern described in Groes, Kircher and Manovskii (2010), yet I cannot reject the hypothesis that the coefficients for quintiles 2-5 are equal.

Another key finding that supports the importance of hierarchical levels is the effect of level on outcomes for unemployed workers. 18.3% of workers who pass through unemployment in my estimation sample return to a lower level than they were in before unemployment. These workers suffer an average wage loss of 13.8%, compared to the 1.1% wage loss suffered by workers who return to the same or a higher level. These results suggest that a significant fraction of wages lost during unemployment are the result of the worker being unable to return to their preferred level after unemployment. I further investigate this effect by performing a regression of wage change during unemployment on worker characteristics, occupation, industry, unemployment duration, and dummy variables for whether the worker's occupation changed during unemployment and whether the worker returned to a lower level than before unemployment (i.e. suffered a "demotion"). I find that wage losses during unemployment are approximately 10% higher for workers who return to a level lower than their pre-unemployment level. This result holds even when controlling for initial occupation, final occupation, and occupation change at the three-digit level. Thus, it appears that workers coming out of unemployment are significantly impacted by where in the hierarchy they return. I investigate the possibility that search frictions cause this result in the model estimated in this chapter.

Task usage provides another strong motivation for the separation of occupations into levels. Since detailed task usage information is typically unavailable in panel data sets, including the NLSY and the GSOEP, researchers are forced to assign task usage based on some observed characteristics in the longitudinal data. Typically, this has been the worker's occupation. However, what this necessarily means is that all workers in the same occupation have the same task usage, which is unlikely to hold. Indeed, Autor and Handel (2013) find task usage varies significantly both within and between occupations.[16] Specifically,

[16]See also Gordo and Skirbekk (2013) which investigates changes in task usage over time in the GQCS.

Table 3.6: Unemployment Wage Change and Hierarchical Level Change

	(1) ISCO	(2) WC/BC
Experience	−0.012	−0.010
	(0.010)	(0.009)
Experience^2	0.024	0.017
	(0.026)	(0.023)
Age	0.019	0.012
	(0.022)	(0.019)
Age^2/100	−0.026	−0.016
	(0.027)	(0.023)
Unemployment Duration	−0.026	−0.030*
	(0.015)	(0.013)
Occupation Change	−0.037	−0.008
	(0.036)	(0.048)
Demotion	−0.090*	−0.100**
	(0.041)	(0.035)
Observations	528	528
R^2	0.418	0.244

Standard errors in parentheses. Dependent variable is change in log wages during unemployment spell, 2009 Euros. Column (1) measures occupation using ISCO-88 codes, while column (2) uses blue-collar/white-collar codes. Demotion refers to a worker returning to a lower level than before unemployment. Time variables measured in years. All regressions include year, occupation and industry dummy variables. Source: German Socio-Economic Panel, 1984-2009.
* $p < 0.05$, ** $p < 0.01$

they find that both employment characteristics such as experience, and worker characteristics such as education, race, and gender, have statistically significant impacts on abstract, routine and manual task usages, even when controlling for occupation. From this we can conclude that assigning task usage based solely on a worker's occupation misses a potentially significant amount of task variation.

I perform similar analyses using the German Qualification and Career Survey. The following results include both men and women but excludes East German workers, while the sample used to assign tasks includes only men.[17]

[17] While the size of the coefficients change if I consider only men, the qualitative results hold.

Since the GQCS is a survey of workers, I am able to examine what characteristics of both the job and of workers impact the task usages that the worker reports. This is in contrast to a data set such as the DOT where task usage is given only by occupation and does not allow for investigation of task usage variation within occupation. I analyze the cognitive and manual tasks separately. I regress the worker's task usage, which equals 1 if the worker performs that task and 0 otherwise, on several worker characteristics, occupation, industry code, and hierarchical level. I repeat this analysis for blue-collar and white-collar, since the level division is particular to those categories.

The results of these regressions are shown in Table 3.7. Similar to Autor and Handel (2013), I find that characteristics other than occupation are statistically significantly related to the probability that a worker reports performing a given task. These include age, potential experience, education, and sex. Most important to this chapter, I find that the worker's reported hierarchical level has a significant effect for each of the tasks. Cognitive task usage increases with level while manual task usage decreases with level in the overall sample as well as in the blue-collar and white-collar subsamples. These effects are also non-trivial in size: for example, a level 3 worker has a 24.1% higher probability of performing the cognitive task, controlling for their occupation, industry, and worker characteristics, compared to a level 1 worker. Thus, a worker's hierarchical level has a large impact on their task usage, which motivates incorporating hierarchical level into the task assignment procedure. Also, though these

Table 3.7: Task Usage and Hierarchical Level

	Cognitive			Manual		
	All	BC	WC	All	BC	WC
Female	0.021**	0.029**	0.010**	−0.018**	−0.035**	−0.010
	(0.004)	(0.011)	(0.004)	(0.005)	(0.006)	(0.007)
Age	0.004**	0.003*	0.001	−0.002*	0.001	−0.004*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
$Age^2/100$	−0.005**	−0.006**	−0.001	0.001	−0.002	0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Middle Level	0.108**	0.114**	0.077**	−0.033**	−0.012**	−0.035**
	(0.005)	(0.009)	(0.005)	(0.005)	(0.005)	(0.009)
Upper Level	0.241**	0.449**	0.109**	−0.072**	−0.037**	−0.058**
	(0.006)	(0.013)	(0.005)	(0.007)	(0.007)	(0.010)
Observations	42,656	18,014	24,642	42,656	18,014	24,642
R^2	0.562	0.253	0.287	0.485	0.203	0.285

Standard errors in parentheses. Dependent variable is binary, and equals one is the worker reports using the task, and zero otherwise. BC refers to the blue-collar occupation while WC refers to white-collar. All regressions include education level, occupation, and industry dummy variables. Source: German Qualification and Survey, 1986 and 1992 waves.
* $p < 0.05$, ** $p < 0.01$

data are only cross-sectional, it does suggest that a worker moving to a higher level within their occupation changes the tasks that they perform, which is a dimension of task change that has not previously been considered.

3.3 Model

In this section I describe the model. Estimating a structural occupational choice model allows me to run counterfactual simulations and assess the importance of the different sources of skill accumulation to wage growth, and the effect that including levels has on this specificity. My occupational choice model is similar to Keane and Wolpin (1997). While that paper considers both schooling and work decisions, I consider only labor market outcomes after schooling is complete.

3.3.1 Environment

The labor market consists of J occupations, where each occupation has L different levels.[18] Workers enter the labor market in unemployment. An unemployed worker has probability ϕ_1 of receiving a job offer at the beginning of the period. This offer comes from a single occupation-level. With probability ϕ_{j+1} the offer comes from occupation j. The offer probability varies by hierarchical level, where κ_1^j and κ_2^j are the probabilities that an occupation j offer is from levels 1 and 2, respectively. The offer probability from level 3 thus is $(1 - \kappa_1^j - \kappa_2^j)$. Note that these values are allowed to vary by occupation j. An unemployed worker that receives no job offer stays in unemployment for another period, while an unemployed worker that receives an offer from occupation j, level l has the option of moving to that occupation-level or remaining in unemployment.

Once employed, a worker faces an exogenous job destruction rate of ψ^j. Again, note that this rate is allowed to vary by occupation. If an unemployed worker is hit with this job destruction shock, they are immediately able to receive a job offer with the same probability as an unemployed worker. As a result, some workers who experience job destruction are actually re-employed immediately and are not recorded as unemployed. Without this feature, all unemployment spells would be a minimum of one year due to the model being yearly. Some workers who in the data do not pass through unemployment

[18] It is not restrictive to assume a common number of levels when fairly aggregated occupation groups are considered. At a three-digit disaggregation level, however, this assumption would not hold without amalgamating the number of levels.

likely do suffer a job destruction, but are quickly or immediately re-employed, which is possible with this specification.

If an employed worker does not suffer job destruction, they have probability ν_1^j of receiving a within-occupation job offer. These offers allow the worker to move across levels within their occupation, where the distribution of these offers by level is determined by the κ values re-weighted to exclude their current level.[19] Finally employed workers whose job is not destroyed and do not receive a within-occupation offer have probability ν_2^j of receiving an across-occupation offer, with the same κ determining the probability distribution across levels. Note that these offer arrival rates are allowed to vary by occupation j. Regardless of job offer outcome, the worker has the option of moving into unemployment. Conditional on not suffering job destruction, an employed worker can choose to stay in their current occupation-level. Finally, all workers have a finite lifetime of T years.

3.3.2 Tasks and Skills

Each occupation-level has a task usage vector which describes what work is performed in that job. I consider two tasks and corresponding skills, Cognitive and Manual.[20] The occupation j, level l task usages are $\boldsymbol{\tau}_{jl} = (\tau_{jl}^c, \tau_{jl}^m)$. These values represent the relative usage of a task in an occupation-level, and

[19]For example, a within-occupation job offer for a blue-collar level 2 worker has probability $\frac{\kappa_1^{BC}}{1-\kappa_2^{BC}}$ of being from level 1, and a probability $\frac{1-\kappa_2^{BC}-\kappa_1^{BC}}{1-\kappa_2^{BC}}$ of being from level 2.

[20]Yamaguchi (2012) and Sanders (2012) both include only Cognitive and Manual tasks.

thus are bounded between zero and one and sum to one.[21] Also, task usage is constant over time.[22] Corresponding to the cognitive and manual tasks, each worker i has cognitive and manual skill levels in period t, which I denote as $\boldsymbol{s}_{it} = (s_{it}^c, s_{it}^m)$.

Each worker is endowed with an initial (unobserved) vector of skills at labor market entry which they apply to tasks to produce output. The earliest a worker can enter the labor market is age 18. I assume that the worker's skills remain unchanged between ages 18 and when they enter the labor market. While this would be problematic if more education groups were included, because I consider workers with at most 13 years of education, 96% of my workers have entered the labor market by age 20.

The initial skills per worker are drawn from normal distributions:

$$s_{i1}^k \sim N(\mu_k, \sigma_k),\ k \in \{c, m\} \tag{3.1}$$

These skills grow over time, depending on the worker's current task usage in a job.[23] The law of motion for skills is:

$$s_{i,t+1}^k = s_{it}^k + \frac{(R_k \tau_{jl}^k)}{1 + \gamma t} - \delta_k,\ k \in \{c, m\} \tag{3.2}$$

[21]This is a common assumption in the task literature. This includes Gathmann and Schönberg (2010), which uses the same task data as this chapter, as well as Lazear (2009).

[22]This assumption is data driven as the task data are only comparable across two waves.

[23]This is a common assumption. For example, Yamaguchi (2012) and Sanders (2012) demonstrate that task usage does indeed affect worker skill accumulation.

where R_k is a scalar that determines the impact of task usage of skill k on the growth of skill k, where $k \in \{c, m\}$ represents cognitive or manual. δ_k is the rate of depreciation of skill k. In order to match the concave shaped of lifecycle wages, I allow the rate of skill change to be a function of period through parameter γ. Conditional on occupational choice (that is, task usage vector), skills change in a deterministic manner.[24]

Workers also accumulate occupation-specific skills, where worker i's period t occupation j skill level is denoted as x_{it}^{j}. Workers enter the labor market with zero occupation-specific skill level in each occupation, i.e. $x_{i1}^{j} = 0$ for all i and j. Occupation-specific skills evolve in a similar manner as transferable skills, where the task-usage of an occupation skill is always one within that occupation, and zero outside. Thus, occupation-specific skills evolve according to:

$$x_{i,t+1}^{j} = x_{it}^{j} + \frac{(R_j)}{1 + \gamma t} \tag{3.3}$$

if the worker is currently in occupation j, and $x_{i,t+1}^{j-1} = x_{it}^{j-1}$ otherwise, and where R_j describe the rate of occupation j skill change. Note that this value is allowed to vary by occupation, reflecting the empirical evidence suggesting that occupation-specific human capital differs in importance across occupations. The entire set of occupation-specific skills for worker i in year t is referred

[24]Sanders (2012), Jovanovic and Nyarko (1996) and Nagypal (2007) all allow for the skill accumulation rate to change with age.

to as $\boldsymbol{x}_{it}$. The worker's state space is their task-specific skill levels, $\boldsymbol{s}_{it}$, their occupation-specific skill levels, $\boldsymbol{x}_{it}$, and their current occupation-level (or unemployment) status. I refer to the collection of state variables as $S_{it} = \{\boldsymbol{s}_{it}, \boldsymbol{x}_{it}, j, l\}$. All information is symmetric and there is no uncertainty by the worker or employer about the worker's skill levels, though these skill levels are unobserved by the econometrician.

3.3.3 Wages

A worker's wage is a function of several elements. First, a worker's task-specific skill level, $\boldsymbol{s}_{it}$, interacts with the task usage of the job, $\boldsymbol{\tau}_{jl}$. Second, the worker's occupation-specific skill x^j_{it} contributes to output.[25] Lastly, there is a random wage component, $\boldsymbol{\epsilon}_{it}$. This stochastic variable is a $J * L + 1$ vector with a value for each occupation-level and the non-employment state. It affects the worker's wage in the employed states, and the worker's non-pecuniary utility in the non-employed state. In addition, it is observable by the worker prior to making their next period decision. Worker i's log wage in occupation j, level l, in period t is given by:

$$w_{ijlt} = s^c_{it}\tau^c_{jl} + s^m_{it}\tau^m_{jl} + x^j_{it} + \epsilon_{jlt} \tag{3.4}$$

[25] Again, it is convenient to think of the worker's occupation-specific skill as a type of transferable skill where the task usage equals exactly one in the given occupation, and zero in every other occupation.

There is no saving or borrowing, so an employed worker i's period t utility, $u_{jlt}(s_{it}, x_{it})$, equals their wage. Unemployed workers receive a non-pecuniary benefit λ, plus the random shock component ϵ_{0t}. Workers discount the future at the rate β.

The worker's decision problem is to maximize their present value of discounted lifetime utility by selecting their occupation-level each period, conditional on their current occupation-level or being in unemployment and the presence of an offer from another occupation-level. Their choice of occupation-level affects not only their wages (or unemployment benefit) in the current period, but also their accumulation of both task-specific and occupation-specific skills. Thus, the worker might sacrifice current wages in favour of the accumulation of skills, which increases future wages. This also applies to unemployment: a worker might choose employment, even if the estimated unemployment benefit is relatively high, due to the effect such a decision would have on their continuation value. For brevity I omit the value function specification, given in Appendix B.2.

3.4 Estimation

I use indirect inference to estimate the model parameters. One of the main motivations for using indirect inference is data related. While other occupational-choice models, such as Keane and Wolpin (1997), use the NLSY as a data source, I use the GSOEP since it contains hierarchical position information. The NLSY follows workers from labor market entry. The GSOEP, however, is representative of the entire population at each survey date. As a result, only a small number of workers are observed from labor market entry. Essentially, this amounts to a missing data problem. I overcome this difficulty by simulating 4550 worker histories from labor market entry to age 60, and selectively sampling from these histories in order to make the sampled simulated data set structurally resemble the true data set in several key dimensions. I discuss this procedure in more detail in Section 3.4.3. I start by discussing how I aggregate occupations, then I proceed to discuss inference inference and the simulation procedures.

3.4.1 Occupation Aggregation

Due to the computational burden of estimating discrete choice dynamic models, the number of occupations must be significantly aggregated.[26] Also, as I subdivide each occupation into three levels, I am further restricted in the number of occupations that I can include and still estimate parameters in a reasonable amount of time. Since the occupational position question is blue-collar/white-collar dependent, I use blue-collar and white-collar as my occupations. Therefore, I have two occupations with three levels per occupation, for a total of six

[26]Keane and Wolpin(1997) uses only white-collar, blue-collar and military, with home and school options. Lee and Wolpin (2006) include white-collar, blue-collar, and pink-collar occupations, in both the service and goods sectors, and Sullivan (2010) includes five occupations.

occupation-levels.[27]

Since the hierarchical level question differs for blue-collar versus white-collar workers, the two are not directly comparable. Thus, it is important to assign workers' occupations as closely as possible along the blue-collar/white-collar dimension. However, since the workers self-report their hierarchical level and blue-collar/white-collar status, assigning the worker's occupation using that question is problematic as it increases the chance of occupational miscoding and spurious occupation changes. This leaves two conflicting goals: comparable level assignment versus accurate occupational classification (and thus accurate occupation changes). I address this issue by allocating workers based on their one-digit ISCO-88 occupation category.[28] For eight of the nine one-digit ISCO-88 categories, over 80% of the workers identify themselves as either white-collar or blue-collar. As a result, I assign all workers in those occupation groups to blue-collar or white-collar, depending on which is the most prevalent. This compromise allows for an accurate hierarchical level assignment for the vast majority of workers, while preserving the more accurate occupational categorization, which helps to better identify occupational mobility and avoid spurious changes.[29]

[27] In terms of employment choices, this is greater than both Keane and Wolpin (1997), which includes only blue-collar, white-collar, and military, and Sullivan, which includes five occupations. Both works include a schooling and unemployment decision. Future work will include expanding the number of occupations and levels.

[28] This approach relies on the assumption that the interviewer is better and more consistently able to assess the workers' occupation codes than the workers themselves.

[29] Previous versions of this chapter used the hierarchial level question itself to assign occupation. While a valid option, that procedure leads to a great deal of spurious occupation changes. As a result, this version opts for using the occupational code to assign occupation.

While eight of the nine occupations can confidently be grouped into either the blue-collar or white-collar categories, ISCO-88 group 5, "Service workers and shop and market sales workers", is more difficult to allocate. As 31% of workers in this group identify themselves as blue-collar, it seems inappropriate to assign all workers in this group into either white-collar or blue-collar. I address this problem by using the three-digit code for workers in this major occupation group. Workers in three-digit groups 511, 513 and 516, and two-digit group 52, report being white-collar with 85%, 87%, 90%, and 73% probability, respectively, and so are allocated to that occupation. Workers in 512 and 514 are more difficult to assign, but since they are slightly more likely to be blue-collar, they are assigned to that occupation. These difficult to assign workers represent only about 2% of the overall sample. A potential cause for concern with this procedure is that, since the occupational allocation is done in a more narrow manner for workers in major group 5, occupational mobility might be artificially higher if workers move between occupations within this major group. Investigating mobility patterns, however, reveals that workers move between the categories within the "Service workers" group infrequently, so there is little concern that narrowing the occupational allocation for this group will produce artificially higher mobility.

3.4.2 Simulation and Indirect Inference

In order to simulate worker careers, I use Chebyshev interpolation to estimate a worker's continuation value.[30] The random component of wages follows an extreme value distribution, with variance parameter ξ.[31] Starting in the final period, I solve the problem using backward induction: I first estimate the Chebyshev coefficients in period T, then I move to period $T-1$, where I use the period T Chebyshev coefficients to estimate the continuation values. This allows me to estimate the period $T-1$ Chebyshev coefficients, which I in turn use in period $T-2$. This process is repeated until the first period is reached. Then, using these coefficients, worker histories can be quickly simulated.

Indirect inference involves choosing parameters to make the simulated data resemble the observed data through the lens of an auxiliary model. This model consists of several moments that capture aspects of the observed data the model is attempting to match, e.g. wage growth, occupation-level make-up, etc. For each parameter guess, N sets of worker histories are simulated.[32] Denote the set of parameter estimates as $\hat{\theta}$. The function $g(\hat{\theta})_n$ maps the parameter estimates to the moment estimates for simulation number $n \in N$, and $\hat{g}$ is the moment values from the observed data. I average across the N sets of moments, $g(\hat{\theta}) = (1/N)\sum_n^N g(\hat{\theta})_n$. The objective is to choose $\hat{\theta}$ to minimize the

[30] Thanks to Salvador Navarro for providing the Fortran code used in the interpolation.
[31] This assumption simplifies the computational burden, since the integral is closed form.
[32] I set $N = 4$ for my estimation.

following function:

$$\hat{\theta} = \arg\min_{\hat{\theta}} (g(\hat{\theta}) - \hat{g})' W (g(\hat{\theta}) - \hat{g}) \tag{3.5}$$

The weighting matrix used is the diagonal matrix of the inverse of the standard errors of the moment conditions.[33] I estimate the standard errors using bootstrapping, with blocking at the individual level. This means that, instead of selecting a particular worker-year observation to include, I select (with replacement) entire worker histories for each bootstrap sample. In total, I use 10,000 samples to estimate the weighting matrix.[34] I describe the moment conditions used in the estimation in Section 3.4.4. Lastly, I set the worker's discount rate, β, to 0.95.

3.4.3 Sampling Method

In order to properly perform indirect inference, the observed and simulated data must structurally resemble each other as much as possible. Two steps are required for this procedure. The first step involves simulating each worker's labor market history. This requires me to assign each worker an initial skill level, and a labor market entry age. I do this by first drawing three random numbers for each worker. The first two random numbers drawn for each worker determine their initial, i.e. age 18, cognitive and manual skill levels, distributed

[33] See Blundell et al. (2008)

[34] This matrix is calculated only once at the beginning of the estimation process.

according to Equation (3.1). Next I assign each worker a labor market entry age using the third random number.[35] This assignment is done such that the distribution of labor market entry ages resembles the distribution in the observed data.[36] Given these values, I can then simulate each worker's labor market history.

While I observe my entire simulated data set, I do not perform indirect inference using all of the simulated data since its structure does not match the GSOEP. Matching the structure of the GSOEP requires drawing an additional pair of random numbers for each worker which determine the sampling characteristics of that worker's labor market history. The first random number is used to assign each worker a sample entry age, when they are first "observed". As with labor market entry age, these values are chosen to match the population distribution. Given this entry age, I select the number of years each worker is observed using the second random number. All observations lying outside of this range are ignored and considered as unobserved for the purposes of indirect inference. When constructing variables such as experience in an occupation, I use only values that I can "see", since this is what I must do

[35]I assume that skills are unchanged during the period after age 18 when the worker is not yet in the labor market. If the model were to include more educated workers, this would be problematic, since the distribution of initial wages for these workers strongly suggests that later labor market entry is correlated with higher skills upon labor market entry. However, for the lower-educated group, the vast majority enter the labor market in the first two to three years, so I do not view this as an issue for this group.

[36]I determine the distribution of labor market entry by analyzing male workers in the GSOEP who are observed for every year between ages 18 to 30 and who eventually enter the labor market.

in the observed data. Thus, while this procedure causes me to lose information regarding the simulated sample, it is necessary since I do not have this information in the observed data. I then search for the set of structural parameters that solve Equation 3.5, i.e. the parameters that minimize the objective function. This yields my set of structural parameters, $\hat{\theta}$.

3.4.4 Auxiliary Model

Indirect inference proceeds by choosing the model parameters that make the simulated data as similar to the observed data as possible, where "similar" refers to the moments of the auxiliary model. While identification of each of the model parameters does not, strictly speaking, come from a single moment condition, nonetheless the moments are chosen to convey relevant information regarding one or a set of parameters. In this section, I describe the moments used in my auxiliary model and how they help to identify my model parameters.

Workers' initial skill levels are drawn from iid distributions $N(\mu_c, \sigma_c)$ and $N(\mu_m, \sigma_m)$. To help identify these parameters, I use the mean and variance of initial worker earnings for each occupation-level. Initial earnings are used since worker's wages are not yet significantly affected by skill accumulation. I restrict myself to at most the first observed wage per individual, and force that wage to be observed within the first seven years in the labor market.[37] Variation in task usage across occupation-levels helps to separately identify the

[37] Since level 3 of each occupation is comparatively sparse in the initial few years, I allow the first wage to be observed in the first 12 years for these occupation-levels.

mean and variance parameters of the initial skill distributions, thus the initial mean and variance of wages of each occupation-level are included separately.

Several wage variance moments are used to identify ξ, the variance parameter of the random component of wages and non-pecuniary returns. These include the variance of initial wages discussed above, as well as overall wage variance. In addition, I include the mean individual lifetime wage variance and the variance of individual wage change between years, all of which help to pin down ξ.

Initial wage levels also help to identify the unemployment benefit parameter λ.[38] In addition, I perform a linear probability regression of employment to unemployment transition, controlling for previous period wage:

$$empunemp_{it} = \beta_0^1 + \beta_1^1 w_{it} + \epsilon_{it}^1 \tag{3.6}$$

where $empunemp_{it}$ equals 1 if worker i transitioned from employment to unemployment between periods t and $t+1$, and zero otherwise. The coefficients from this regression are included in my model as auxiliary parameters. Although some employment to unemployment transitions are involuntary, some are voluntary. Thus, controlling for current wage level helps to identify λ. In addition, I include the mean level of wage prior to an unemployment spell, and mean wages immediately following an unemployment spell. Again, this helps to identify λ since a higher λ makes unemployment more attractive to

[38] See Yamaguchi (2010).

employed workers, raising the wage level at which workers will be willing to move into unemployment, while increasing the wage level required to induce workers to exit unemployment.

There are a number of events and corresponding probabilities in my model, including unemployment to employment, employment to unemployment, and both within- and across-occupation changes. To identify the job destruction rates ψ^{BC} and ψ^{WC}, I include the employment to unemployment probability rates by occupation. Also, the constant term in regression (3.6) help to identify this parameter. I include the unemployment to employment rate by destination occupation-level to help identify the offer arrival rate in unemployment, ϕ_1, the distribution of job offers by occupation, ϕ_2, and by levels, the κ's. In addition, I include unemployment make-up in ages 18, 19, and 20. Since workers enter the model in unemployment, the changes in the unemployment rate in the first several years helps to pin down the unemployment job offer arrival rate. Within-occupation arrival rates, ν_1^{BC} and ν_1^{WC}, are identified by including promotion and demotion rates by occupation. Lastly, the across-occupation arrival rates, ν_2^{BC} and ν_2^{BC}, are estimated using occupation change rates by occupation and level. I also include occupation change rates by occupation and age range to capture the observed declining pattern of occupation change over the lifecycle.

In addition to the rate of change moments, I perform a linear probability regression of occupation change:

$$occchange_{it} = \beta_0^2 + \beta_1^2 t + \beta_2^2 \mathbb{1}(l=1) + \beta_3^2 \tau_{i,t-1} + \epsilon_{it}^2 \tag{3.7}$$

I control for period t, an indicator variable $\mathbb{1}(l=1)$ which equals one if the initial level equals 1, and the initial occupation-level's cognitive task, $\tau_{i,t-1}$. One of the central motivations for including hierarchical level in an occupational choice model is that a worker in the lower level has a significantly higher probability of changing occupations. Thus this is a an important moment to match to the observed empirical facts.

I include non-constant coefficients from linear probability regressions for each occupation-level. These regressions take the form:[39]

$$d_{it}^{jl} = \beta_0^3 + \beta_1^3 t + \beta_2^3 t^2,\ j \in \{BC, WC\}, l \in \{1,2,3\} + \epsilon_{it}^3 \tag{3.8}$$

where d_{it}^{jl} is an indicator that equals 1 if worker i is in occupation-level jl in period t, and 0 otherwise. These regressions help to match the overall pattern of occupation-level make-up in the data. In particular, they help to properly identify the probability parameters. If, for example, the blue-collar probability ϕ_2 was too low, then there would be too few workers in blue-collar jobs, at least initially, which would not match the patterns from the regressions. Also, I include the fraction of workers in each occupation-level for age ranges 18-30,

[39] I include period only linearly for blue-collar level 1 and white-collar level 3, since that specification better matched the observed data.

31-50 and 51-60. These moments help my model to fit the overall patterns in the data.

The final group of parameters to discuss are those related to skill change. Identification of these parameters comes primarily from considering wages. First, I include a Mincerian fixed effect wage regression of the following form:

$$\begin{aligned} w_{it} \;=\;& \beta_1^4 t + \beta_2^4 t^2 + \beta_3^4 exp_{1,it} * \mathbb{1}(j=1) + \beta_4^4 exp_{1,it}^2 * \mathbb{1}(j=1) + \beta_5^4 exp_{1,it}^3 * \mathbb{1}(j=1) \\ & + \beta_6^4 exp_{2,it} * \mathbb{1}(j=2) + \beta_7^4 exp_{2,it}^2 * \mathbb{1}(j=2) + \beta_8^4 exp_{2,it}^3 * \mathbb{1}(j=2) \\ & + \beta_9^4 exp_{it} + \beta_{10}^4 exp_{it}^2 + \beta_{11}^4 \tau_{it} + \beta_{12}^4 cogsum_{it} * \tau_{it} + \beta_{13}^4 cogsum_{it}^2 * \tau_{it} + \epsilon_{it}^4 \end{aligned} \tag{3.9}$$

where $\mathbb{1}(j=1)$ and $\mathbb{1}(j=2)$ are indicator functions that equal 1 if worker i is in the given occupation in period t, and zero otherwise, $exp_{j,it}$ is the worker's experience in occupation j at time t and exp_{it} is overall experience. In addition, $cogsum_{it}$ refers to the sum of a worker's cognitive task usage. For example, if a worker is employed in an occupation-level with a cognitive task usage of 0.5 in period 1 and 0.6 in period 2, then $cogsum$ in period 3 would be 1.1.

This regression contains several elements that all help to identify specific elements of the model. First, since this model contains a search component, t and t^2 are included to help identify this search process. Even without skill level change, wages would be expected to, on average, increase with age as workers move to better matches for their skills. Second, workers accumulate occupation-specific skills at a rate that (potentially) differs between occupations. Thus, the occupational experience, interacted with a dummy term for their current occupation, is included. This allows for occupational experience to have differential impacts on their wages depending on the occupation, and helps to identify the R_{BC} and R_{WC} parameters. Third, overall experience terms are included to help match overall change in worker skill over time. These terms provide information regarding all of the skill growth as well as depreciation parameters. The model predicts, however, that the type of experience, i.e. previous task usages, will impact wages. Also, the impact of this task-weighted experience depends on the current task usage. Thus, the fourth and final set of regressors include the cognitive task usage, the cognitive sum (described above) interacted with cognitive task usage, and the square of their cognitive sum interacted with cognitive task usage. Including these regressors provides important information useful for disentangling the growth rate of cognitive (R_c) versus manual (R_m) skills.

I also include as moments the mean wage levels at different points in the lifecycle for each occupation-level. These moments help the model to better match the observed wage patterns. Also, they help to pin down the curvature parameter on skill change, γ. I choose the years to be representative of the overall lifecycle pattern and so include mean wage level at age 29-31, 39-41, and 54-56. Three-year ranges are included since, for some occupation-levels, there may be few workers present.

Since the skill change parameters have direct implications for wage changes, I also include coefficients from a wage change regression in the auxiliary model:

$$\Delta w_{it} = \beta_0^5 + \beta_1^5 \frac{1}{log(t)} + \beta_2^5 \frac{1}{log(t)} * \tau_{i,t-1} * \tau_{i,t} + \beta_3^5 exp_{j,it} + \epsilon_{it}^5 \tag{3.10}$$

where Δw_{it} is worker i's wage change between periods $t-1$ and t, and $\tau_{i,t-1}$ and $\tau_{i,t}$ are worker i's cognitive task usage in periods $t-1$ and t respectively. The model specification predicts that wage change between periods depends both on current task usage as well as last-period's task usage. This is due to the fact that last period's task usage determines the change in the skill level, while current task usage determines payoff from this change in skill. This change, however, depends on the worker's age, which enters the equation in an inverse-log form. Thus, I include the inverse log period as a regressor as well as interacted with the current and prior task usages. Also, by including prior task usage, I take advantage of worker movement across either level or occupation to help identify the skill change parameters. Lastly, as wages also change due to accumulation of occupation-specific skill, I include the worker's occupational experience as a regressor.[40]

To help match the overall features of the data, especially in terms of mobility across occupations and levels, I include as auxiliary parameters the mean

[40] Unlike the Mincerian wage regression, I do not allow occupation experience to interact with occupation. This is because, in the observed data, I found that such a control produced little difference in coefficient value or model fit.

change in worker wages for the following events: no change, promotion, demotion, occupation change, and unemployment.

Lastly, I include coefficients from a regression of the wage change during unemployment. These help to identify the skill depreciation terms. In addition, I motivate hierarchical levels by showing that workers who experience "unemployment demotions" suffer significantly higher wage losses than those who return to the same or higher hierarchical level than their pre-unemployment level. This regression is as follows:

$$\Delta w_{it}^{un} = \beta_0^6 + \beta_1^6 \mathbb{1}(undur_{it} > 1) + \beta_2^6 t + \beta_2^6 unempdemot_{it} + \epsilon_{it}^6 \tag{3.11}$$

where Δw_{it}^{un} is worker i's wage change during the unemployment spell that ended in period t, $\mathbb{1}(undur_{it} > 1)$ is an indicator function that equals one if the unemployment spell was greater than one year, and zero otherwise, and $unempdemot_{it}$ is an indicator variable that equals one if the worker returns to a lower hierarchical level than prior to unemployment.[41] Wage changes during unemployment for two reasons. First, skills depreciate, and the amount of depreciation depends on the length of unemployment. Thus, including unemployment duration in this regression helps to pin down the skill depreciation terms. Second, due to search frictions, workers cannot return to their preferred occupation-level immediately. As a result, workers who return to a lower level

[41]A categorical variable is included since there are only a small number of unemployment spells that last longer than a year.

experience higher wage losses. Period t is included since older workers are expected to have had more time to move into their optimal occupation-level, and thus may suffer higher wage losses due to unemployment.

In addition to wages, it should be noted that the regressions specified by Equation (3.8) will also help to identify these parameters. Consider, for example, if the growth rate in cognitive skill is too high while the growth rate for manual skill is too low. This would cause workers to accumulate "too much" cognitive skill, and thus they would substitute into higher cognitive-task using occupation-levels. Thus, the overall pattern of occupation-level make-up is crucially affected by skill change parameters.

3.4.5 Estimating Standard Errors

Calculating standard errors using a numerical Jacobian is problematic for this model due to the non-smoothness of the objective function. This lack of smoothness results from the discrete choice nature of the model. For example, small changes in the job destruction rate parameter ψ^j will only impact the objective function if a worker's risk of unemployment fell in the small range between the original and adjusted value, which is unlikely, and thus the finite difference method will likely fail. While this issue can theoretically be addressed by increasing the number of simulations, there is no guarantee that this procedure will lead to accurate standard errors. Instead, I turn to a bootstrap procedure. Using the parameter estimates, I simulate Q data sets,[42] and estimate the model parameters for each simulated data set ($\hat{\theta}_q$).[43] These values are then used to estimate the standard errors of the parameters. While computationally intensive, this procedure allows for accurate error terms to be estimated.

In addition to providing standard errors for the parameter values, performing the bootstrap procedure helps to ensure that my model is, in fact, identified. Since the estimation is able to recover with a high degree of accuracy the parameters of the model, this demonstrates that the auxiliary model contains sufficient information to identify the parameters. These results also demonstrate that the sampling procedure is effective: since I drop on average around 3/4 of each worker's occupational history, it is not clear that the remaining data are enough to reliably recover the model parameters. However, as the results demonstrate, this method is effective. Thus, even though I simulate 43 years of data per worker, and I only actually observe at most 25 years per worker (and on average roughly 14 years), I am still able to estimate the parameters of a full life-cycle model.

[42] I use $Q = 40$ data sets in total.

[43] See Sullivan (2010), who also uses this method to calculate standard errors in a structural model.

3.5 Results

I begin my analysis of the estimation results by discussing the parameter estimates. In addition to estimating parameters for the full model, I also estimate parameters for a version of the model without levels.[44] I then proceed to discuss the overall fit of the model. Lastly, I describe the counterfactual exercises that are performed to evaluate the importance of task-specific versus occupation-specific human capital accumulation to wage growth, and I compare the results between the models with and without hierarchical levels to assess the impact of omitting levels from an occupational choice model.

3.5.1 Parameter Estimates

Parameter estimates are shown in Table 3.8. I begin by describing the model with levels. I find that cognitive skill accumulation exceeds manual skill accumulation. In contrast to Yamaguchi (2012) and Sanders (2012), however, the manual growth rate is fairly large. Occupation-specific skill growth is large for the blue-collar occupation but appears to be small for the white-collar occupation. Depreciation impacts the manual skill more so than the cognitive skill, which experiences little depreciation. I also find that cognitive skills are distributed with higher variance than manual skills. The shape parameter governing skill growth, γ, is 0.284. At this value, by age 40, the rate of skill

[44]This requires the simplification of the auxiliary model to remove any level-specific moments. Other than removing moments particular to hierarchical level, the same auxiliary model is used.

accumulation by the worker has fallen to 14% of its age 18 value.

Event probabilities vary to a significant degree between the two occupations. Blue-collar workers experience more than double the job destruction rate of white-collar workers. White-collar workers also receive job offers both within and across firms at a higher rate than blue-collar workers. In both occupations, the probability of receiving a job offer from the highest level is quite low, which matches the overall scarcity of both white-collar and blue-collar level 3 workers.

Overall, the parameter estimates between the model with and without levels are fairly close, with a few important exceptions. Without levels, the model estimates a significantly lower rate of blue-collar occupation-specific skill accumulation, and a correspondingly higher level of manual task-specific skill accumulation. Also, the initial distribution of manual skills has a higher variance in the model without levels. This is likely due to the lower variability in task vector options making the wage variation more difficult to match, and forcing a higher distribution of initial skill levels. The mean of the initial cognitive skill distribution is lower in the model without levels, which again is likely caused by the lack of task usage variation within the occupation forcing the model to reduce the overall cognitive skill levels to match the wage data. Lastly, the across-occupation offer arrival rate for workers in white-collar is significantly higher in the no level model than in the model with levels. This large difference in occupation-specific returns appears to be caused by the model attempting to

Table 3.8: Model Parameter Estimates

Parameters	**Values**	
	Levels	**No Levels**
Skill Change		
Task-Specific		
Cognitive: R_c	0.317 (0.027)	0.332 (0.040)
Manual: R_m	0.100 (0.017)	0.210 (0.039)
Occupation-Specific		
Blue-Collar: R_{BC}	0.107 (0.009)	0.022 (0.018)
White-Collar: R_{WC}	0.019 (0.011)	0.029 (0.016)
Depreciation		
Cognitive: δ_c	0.003 (0.002)	0.006 (0.003)
Manual: δ_m	0.026 (0.002)	0.022 (0.002)
Shape Parameter: γ	0.284 (0.022)	0.305 (0.015)
Initial Skill Distributions		
Cognitive: μ_c	6.942 (0.036)	6.71 (0.041)
σ_c	0.168 (0.019)	0.170 (0.028)
Manual: μ_m	7.028 (0.023)	7.094 (0.023)
σ_m	0.043 (0.09)	0.082 (0.012)
Wage Error Variance: ξ	0.101 (0.002)	0.105 (0.001)
Unemployment Benefit: λ	7.147 (0.053)	7.026 (0.022)
Event Probabilities		
Unemployment Events		
Offer Arrival (Unemployed): ϕ_1	0.507 (0.013)	0.506 (0.021)
Blue-Collar Probability: ϕ_2	0.735 (0.017)	0.796 (0.021)
White-Collar Probability: 1 - ϕ_2	0.265	0.204
Blue-Collar Events		
Job Destruction: ψ^{BC}	0.088 (0.005)	0.069 (0.004)
Offer Arrival (Within-Occ): ν_1^{BC}	0.073 (0.013)	
Offer Arrival (Across-Occ): ν_2^{WC}	0.092 (0.022)	0.085 (0.020)
Level 1 Probability: κ_1^{BC}	0.458 (0.021)	
Level 2 Probability: κ_2^{BC}	0.495 (0.011)	
Level 3 Probability: 1- κ_1^{BC} - κ_2^{BC}	0.047	
White-Collar Events		
Job Destruction: ψ^{WC}	0.041 (0.004)	0.049 (0.005)
Offer Arrival (Within-Occ): ν_1^{WC}	0.104 (0.017)	
Offer Arrival (Across-Occ): ν_2^{WC}	0.308 (0.041)	0.499 (0.162)
Level 1 Probability: κ_1^{WC}	0.446 (0.045)	
Level 2 Probability: κ_2^{WC}	0.461 (0.016)	
Level 3 Probability: 1- κ_1^{WC} - κ_2^{BC}	0.093	

Standard errors in parentheses.

properly match the proportion of workers in each occupation. If I simulate data using the model without levels but take the skill change parameters from the model with levels, the white-collar occupation is significantly underrepresented.

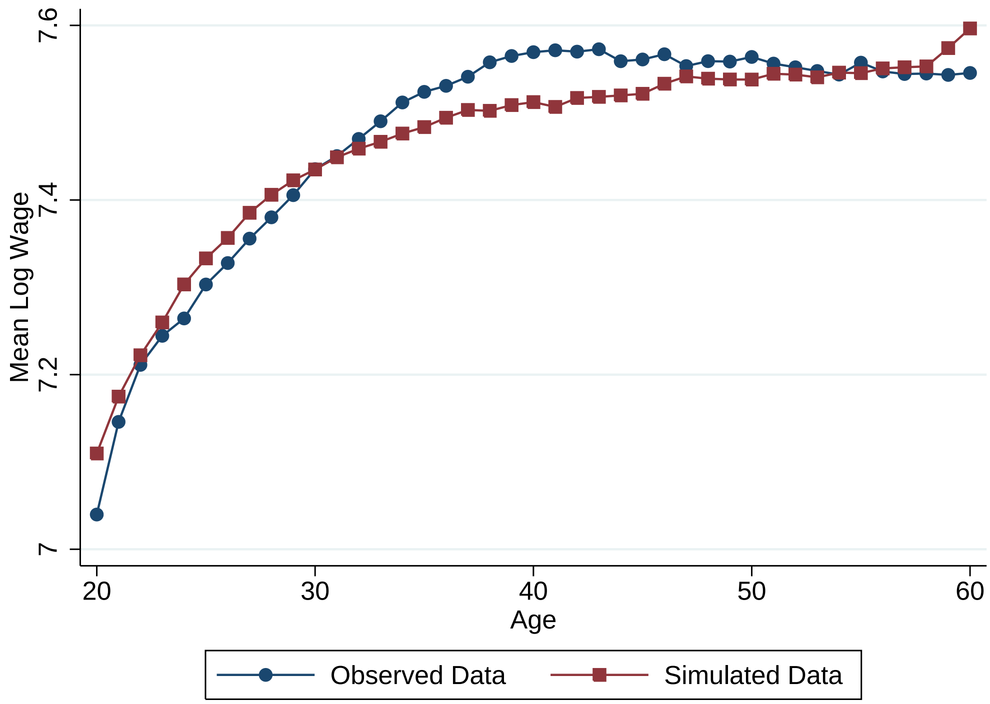
3.5.2 Model Fit

In this section I assess the overall fit of my model. I compare the life cycle wage profiles of the observed data and data simulated using the model parameters, and I examine the auxiliary model moment values. I include key auxiliary moments in this section, and leave the rest to Appendix B.4.

Figure 3.1 shows the overall age-wage profiles from the simulated data versus the observed data. The model fits the pattern well, though the curvature of the profiles differs somewhat. I show the blue-collar and white-collar life cycle wage profiles in Figures 3.2 and 3.3. The blue-collar wage profile is matched extremely well, while the white-collar wage profile does not match as well as the blue-collar profile. The reason for this disparity is likely due to the inclusion of only a single curvature parameter that governs all skill accumulation. These results motivate future work to allow for manual and cognitive task usage accumulation to have different curvature parameters, which should help better match the white-collar wage patterns.

Figure 3.4 shows the fraction of workers in the blue-collar and white-collar

Figure 3.1: Overall Wages



occupations by age. The model matches the fraction of workers in each occupation over the life cycle well. The fraction of workers in blue-collar is matched very well over the entire lifecycle. The white-collar fraction is matched well after age 30, but is overestimated early in the career. This is due to the model understating unemployment initially, which can be seen in Figure 3.5. However, after age 30 the model matches the pattern of unemployment very well, and begins to closely match the fraction of workers in white-collar. I replicate these figures for the model without levels, which are included in Appendix B.3. Both the level and non-level model versions match the occupation fractions and the wage profile for the blue-collar occupation well. However, the non-level

Figure 3.2: Wages: Blue-Collar

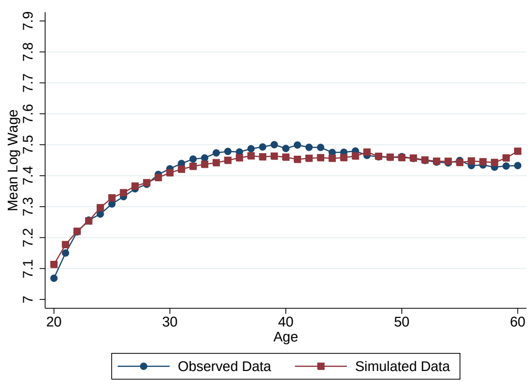


Figure 3.3: Wages: White-Collar

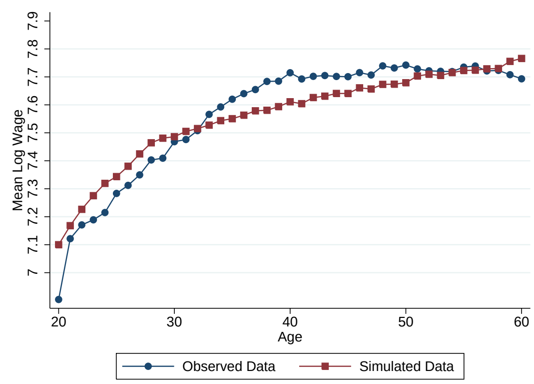


Figure 3.4: Occupation Composition

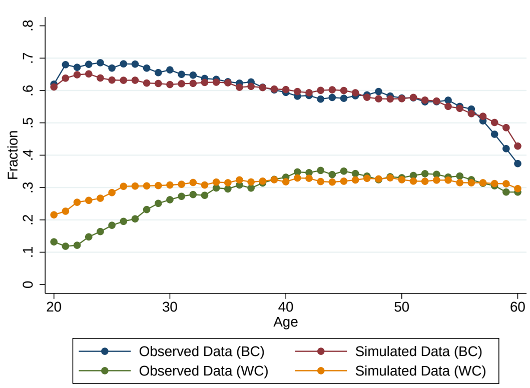


Figure 3.5: Unemployment

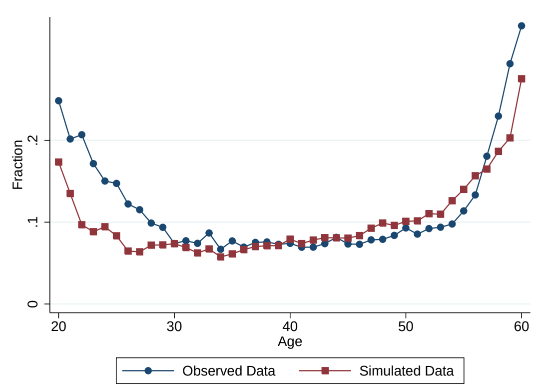


Table 3.9: Auxiliary Model: Wage Change During Unemployment

	Data	Model
$\mathbb{1}(undur_{it} > 1)$	-0.06313	-0.01365
	(0.0263114)	(0.0188719)
t	-0.0049	0.002114
	(0.0012566)	(0.0009503)
$unempdemot_{it}$	-0.11736	-0.11912
	(0.0327483)	(0.0201509)
Constant	0.113199	-0.13039
	(0.0296531)	(0.0271916)
	N = 559	$\bar{N}$ = 1290.5
	R^2 = 0.067	R^2 = 0.031

Table 3.10: Auxiliary Model: Occupation Change Regression

	Data	Model
t	-0.00046	-0.00044
	(0.0000891)	(0.0000806)
$\mathbb{1}(l = 1)$	0.008901	0.012407
	(0.0021413)	(0.0019732)
$\tau_{i,t-1}$	0.032797	0.035915
	(0.0042429)	(0.0038979)
Constant	0.027232	0.020477
	(0.0028657)	(0.0027823)
	N = 38086	$\bar{N}$ = 40052
	R^2 = 0.002	R^2 = 0.003

version does not match the white-collar life cycle wage profile.

Two of the main motivating features of the data are: (1) workers who go through unemployment and return to a lower level suffer larger wage losses on average than those returning to the same or higher level; and (2) workers in the lower hierarchical level are more likely to change occupations. Table 3.9 shows the auxiliary model moments for the wage change during unemployment regression in both the observed and simulated data. The value of note is the $unempdemot_{it}$ coefficient. In the observed data, workers who experience

Table 3.11: Auxiliary Model: Occupation Change Probabilities

	Data	Model
Blue-Collar Level 1	0.021	0.019
Blue-Collar Level 2	0.027	0.024
Blue-Collar Level 3	0.049	0.023
White-Collar Level 1	0.091	0.085
White-Collar Level 2	0.033	0.033
White-Collar Level 3	0.025	0.019

a demotion during unemployment suffer an additional 11.7% wage loss over those who return to the same or higher level. I am able to match this value very closely, as in my simulated data, workers experiencing a demotion in unemployment suffer an additional 11.9% wage loss. Table 3.10 shows the occupation change regression of the auxiliary model. While the coefficient value is slightly too high, I am nonetheless able to match the positive effect that being in the lower level has on occupational mobility. Also, as Table 3.11 shows, I am able to match the increasing occupation change rate by level in blue-collar, and decreasing rate by level in white-collar. These results confirm that my model is able to replicate the observed relationships between hierarchical level, occupational mobility, and wage losses from unemployment.

In the model without levels, wage change during unemployment is positive, which contradicts the empirical observation that wages on average decline as a results of a spell of unemployment. The reason for wages actually increasing is that the job arrival rate is higher for workers in unemployment, which can lead to a better match as a result of passing through unemployment. The model with hierarchical levels, however, is able to match the observation that wages decline during unemployment, due in large part to the presence of hierarchical level search frictions. Therefore, hierarchical levels appear to be an important feature of a model that examines wage losses during unemployment, since their inclusion allows the model to capture a significant source of wage losses.

3.5.3 Counterfactuals

One of the primary motivations for estimating a structural model is that I can run counterfactual simulations to quantify the relative contributions of task-specific versus occupation-specific human capital to wage growth, and I can compare these estimated values between the model with and without hierarchical levels. I run four simulations: (1) a baseline simulation at the estimated parameter values; (2) a counterfactual simulation where task-specific skill growth rates R_c and R_m are set to zero; (3) a counterfactual simulation where the occupation-specific skill growth parameters R_{BC} and R_{WC} are set to zero; and (4) a counterfactual simulation where both task-specific and occupation-specific skill growth rates are set to zero.

I simulate 10,000 worker histories for each of the four cases and I compare the average log wages in each. This is done separately for the model with levels and the version without, and also separately by occupation. The mean log wage levels from these simulations are shown in Table 3.12. The overall mean log wage from the baseline simulation with levels is 7.478. Eliminating task-specific skill growth reduces the mean log wage to 7.082, while eliminating occupation-specific human capital accumulation results in a mean log wage of 7.284. This corresponds to a 32.7% drop in overall mean wage level from eliminating task-specific skill growth, while eliminating occupation-specific human capital accumulation causes a 17.6% drop. Thus, while growth of both types of human capital is important to wage growth over the life cycle, it is task-specific human capital that has the most significant effect.

Not surprisingly, since $R_{BC} > R_{WC}$, I find that occupation-specific skill accumulation is more important for wage growth in the blue-collar than white-collar occupation. This is a similar result to one found in Keane and Wolpin (1997), where experience in the blue-collar occupation increased wages more so than experience in the white-collar occupation, controlling for total experience. Eliminating occupation-specific skill accumulation results in mean wage level reductions for blue-collar and white-collar of 35.1% and 16.3%, respectively, while eliminating task-specific skill accumulation causes reductions of 29.2% and 42.3%. The high growth rate of the cognitive skill results in the relatively high importance of task-specific skill accumulation for the white-collar occupation.

I motivate incorporating hierarchical levels by theorizing that allowing for task variation within the occupation and allowing for workers to adjust their task usages without having to sacrifice occupation-specific human capital may have significant effects on the estimated specificity of human capital. I assess the impact that incorporating levels has by comparing the counterfactuals

Table 3.12: Counterfactual Simulations

Model With Levels

	Baseline	No Task Skill	No Occ Skill	No Skill Growth
Overall	7.478	7.082	7.284	6.889
Occupation:				
Blue-Collar	7.442	7.096	7.010	6.845
White-Collar	7.583	7.031	7.405	6.909

Model Without Levels

	Baseline	No Task Skill	No Occ Skill	No Skill Growth
Overall	7.427	7.059	7.343	7.054
Occupation:				
Blue-Collar	7.424	7.202	7.326	7.065
White-Collar	7.432	7.218	7.351	7.049

Cell values are mean log wage levels. First column is the baseline simulation. Second column is the counterfactual with no task-specific skill growth. Third column is the counterfactual with no occupation-specific skill growth. Last column is the counterfactual with no task-specific or occupation-specific skill growth.

with and without levels. I find that there are significant differences between the models in terms of the specificity of human capital. In the blue-collar occupation, occupation-specific human capital is estimated to have much less of an effect for the model without levels, and eliminating accumulation of that skill causes a reduction of only 10.2% in mean wage level compared to 35.1% for the model with levels. For the white-collar occupation, the model without levels significantly understates the importance of task-specific skill accumulation, and the wage reductions from eliminating this skill growth are 42.4% and 19.3% in the models with levels and without levels, respectively. These results show that incorporating hierarchical levels can have an important impact on estimates of the specificity of human capital.

3.6 Conclusion

In this chapter, I document several facts relating to hierarchical level - specifically, that workers in the lower hierarchical level are more likely to experience occupation change, workers who return from unemployment into a lower level suffer higher wage losses, and that task usage within an occupation varies by level, with cognitive tasks usage typically increasing with level. I estimate an occupational mobility model where occupations are composed of hierarchical levels, workers accumulate both task-specific and occupation-specific human capital through learning-by-doing, and where workers face search frictions, in order to match these findings and to quantify the importance of task-specific versus occupation-specific human capital for wage growth. This is done separately for models with and without hierarchical levels, and the results are compared to evaluate what effect including levels has on the estimated specificity of human capital.

I use labor market history data from the GSOEP and task usage data from the GQCS. Estimating the model using indirect inference, I am able to match the empirical observations. Running counterfactual simulations, I find that both sources are important, though task-specific human capital can explain the majority of wage growth, especially for the white-collar occupation. Omitting levels results in a significant understatement of the importance of occupation-specific human capital for workers in the blue-collar occupation. Furthermore, the model without hierarchical levels fails to match wage declines during unemployment. These results demonstrate that omitting hierarchical levels can result in both the specificity of human capital being misestimated, as well as failing to match important labor market outcomes.

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Chapter 4

The Signaling Role of Promotions: New Evidence from European Firms

4.1 Introduction

In this chapter we provide new empirical evidence on the signaling role of promotions. The idea that promotions serve as signals of worker ability was first developed in Waldman (1984) and has significantly influenced the subsequent theoretical literature. The theory is based on asymmetric learning (about worker ability) by employers in a labor market. In most employment relationships, the party who possesses the most accurate and complete information concerning a worker's ability is that worker's own employer. The information possessed by other employers in the labor market is typically less complete. This means that promoting a worker to a higher rank conveys new (and positive) information to other employers concerning the worker's ability, and those employers update their beliefs (and wage offers) accordingly. The current employer must therefore increase the promoted worker's compensation to a sufficient extent to prevent the worker from being bid away by a competitor.

Extending the model of Waldman (1984) to incorporate a worker characteristic that is publicly observed by all firms in the labor market and that is correlated with ability gives rise to testable implications. In DeVaro and Waldman (2012) that worker characteristic is the level of educational attainment.[1] Promotion of a highly-educated worker releases little new information to the market (since other employers already saw the person as having high ability) whereas a promotion of a less-educated worker is more of a surprise to other firms. This greater surprise leads to a big positive update in the beliefs of competing firms about the worker's ability and, hence, a big increase in the wage these employers are willing to offer the worker. To avoid the resulting bidding war, the employer of this less-educated worker may be inclined to withhold a promotion from the worker, even if such a promotion would be justified on productivity grounds. The result is that promotion rates are inefficiently low for less-educated workers, holding job performance constant. By similar logic, the wage increase occurring at the time of promotion should decrease with educational attainment, again holding job performance constant. Furthermore, both of these predictions should hold more strongly for first promotions than for subsequent promotions. The reason is that because a promotion releases

[1]See Bernhardt (1995) for a related theoretical analysis that also differentiats workers by level of educational attainment.

significant information about a worker's ability to other firms in the market, each successive promotion a worker receives reduces the information asymmetry between the worker's current employer and other employers in the labor market. The preceding testable implications are derived formally in DeVaro and Waldman (2012) and serve as the primary basis for the present chapter.

We empirically test the predictions from DeVaro and Waldman (2012), using large-scale, nationally-representative, worker and firm-level panel data from Finland and Germany. The Finnish dataset is a linked employer-employee panel, drawn from the records of the Confederation of Finnish Industries (EK), which is the central organization of employer associations in Finland. Although the full panel spans the years 1981 to 2010, only the years 2001 to 2010 contain suitable information for our analysis. That analysis sample consists of 2364 firms, 86,900 persons (of which 31,572 are female), and 269,559 person-year observations (of which 33.4 percent are female). The German dataset is the German Socio-Economic Panel (GSOEP), an annual panel of households that began in 1984 and that continues to the present (2013).[2] The panel consists of 17,134 households, 55,471 individuals, and a total of 497,087 person-year observations. The advantages of focusing on two distinct countries in the same empirical analysis are highlighted in the following statement from Hamermesh (2007): "If our theories are intended to be general, to describe the behaviour of consumers, firms, or markets independent of the social or broader

[2] Our analysis uses the International Scientific Use Version, which is a 95% subsample of the full panel.

economic context, they should be tested using data from more than just one economy." Following DeVaro and Waldman (2012) we differentiate workers by their level of educational attainment, and we address the aforementioned testable implications related to the probability of promotion and to the wage increases conditional on promotion. We find that the signaling role of promotions is supported in both Finland and Germany in that the predictions from DeVaro and Waldman (2012) hold for certain educational groups.

We also investigate whether and how the signaling role of promotions differs between men and women. A potential theoretical explanation for gender differences in the extent to which promotions signal worker ability can be found in Milgrom and Oster (1987). In that framework there are two types of workers (Visibles and Invisibles). Visibles are workers whose abilities are readily observed by all employers in the labor market, whereas Invisibles are workers whose abilities are difficult to observe by employers other than the worker's current employer. Women (men) are likely to have disproportionately large representation in the Invisibles (Visibles) group. The argument is that for various reasons, such as lack of "old boys club" connections, women are less well connected to the outside labor market. This framework provides a theory of gender discrimination in the labor market, because employers with private information about their highly talented (but Invisible) workers can "hide" these workers from competing firms by failing to promote them. The strategy would not work for Visibles, because withholding promotion from a highly talented

Visible would lead a competing firm to steal that worker away. One implication is that, holding worker performance constant, promotion probability should be lower for women than men.[3] Furthermore, again holding performance constant, the preceding gender difference should be larger for first promotions than for subsequent promotions, for the following reason. Since a promotion releases significant information about ability to competing firms, the informational asymmetry is reduced and "Invisible" women start to look more "Visible" to outside firms. A related implication of the Milgrom-Oster framework is that the wage increase attached to promotion should be larger for women than men, controlling for worker performance, with this result more pronounced for first than for subsequent promotions.

The empirical literature on gender differences in promotion probabilities and in the wage changes attached to promotion has yielded mixed results, though in most cases the empirical models in that literature do not control for time varying, job-specific measures of worker performance.[4] Some studies find a positive gender gap in promotion probabilities, others find a negative gap, and others find no gap. One study that includes a control for worker performance is Blau and DeVaro (2007), which finds a lower promotion probability for women

[3]Lazear and Rosen (1990) offer an alternative explanation for why, holding worker performance constant, promotion probability should be lower for women than men. That explanation is not based on the signaling role of promotion but rather on the idea that differential movement along job ladders entails comparative advantage, and women are assumed to be more productive than men in non-market labor such as household work.

[4]See Blau and DeVaro (2007) for a survey.

than men of 2 to 3 percentage points. That same study finds essentially no gender difference in the wage change attached to within-firm promotion.[5] Drawing on the Milgrom-Oster framework, we can evaluate whether women have lower promotion probabilities than men after controlling for performance, and whether the gender gap diminishes after the first promotion is received. Similarly, we can evaluate whether women experience larger wage increases than men after controlling for worker performance and whether this gender difference is stronger for first than for subsequent promotions. In both Finland and Germany we find evidence of gender differences in promotion probabilities that are of comparable magnitude to those found in Blau and DeVaro (2007), and we also find evidence in both countries that this gender gap dissipates after the first promotion. In the Finnish data the point estimates reveal larger wage increases attached to within-firm promotion for women than men, with this difference larger for first than for subsequent promotions, though these gender differences are statistically insignificant at conventional levels. In the German data we find a positive but statistically insignificant wage increase from within-firm first promotions for men, whereas the corresponding increase for women is considerably larger and statistically significant at the one percent level. In the case of subsequent promotions, neither gender experiences a statistically

[5]Examples of studies that found the same result but without controlling for worker performance include Olson and Becker (1983), Gerhart and Milkovich (1989), and McCue (1996). Other studies found evidence of a gender gap in one direction or the other, though in the absence of a control for worker performance. The gender gap favored men in Hersch and Viscusi (1996), Barnett et al. (2000), and Booth et al. (2003), whereas it favored women in Cobb-Clark (2001).

significant wage change. This pattern of results is consistent with the signaling role of promotions being stronger for women than men, and diminishing after first promotion, consistent with the Milgrom-Oster framework.

A unique feature of our analysis is that we distinguish between within-firm and across-firm promotions. The theoretical literature on promotions and wage dynamics frequently focuses on a unique equilibrium that is characterized by no turnover, so that a worker's initial employer always raises a promoted worker's wage (or a non-promoted worker's wage) to a sufficient extent to prevent that worker from being bid away by a rival firm. Testable implications are then based on this zero-turnover equilibrium, which is seen as a justification for conducting empirical work that focuses only on workers who remain with the firm. The focus on within-firm promotions is convenient, given that in single-firm personnel data sets there is typically no information on workers after they separate from the firm. However, in the real world, turnover regularly occurs, and previous research suggests it is an important aspect of careers (e.g. Topel and Ward 1992, Farber 1994, Booth et al. 1999, Munasinghe and Sigman 2004, and Parrado et al. 2007).[6] The data in the present study allow

[6]Noting the connection between career progression and turnover, Waldman (2007) has called for more empirical work on this subject to guide the development of theories that connect wage and promotion dynamics to turnover. Building on Gibbons and Waldman (1999), Ghosh (2007) provides a theoretical analysis predicting that the probability that a worker switches firms decreases with labor market experience. See also DeVaro and Morita (2013) which provides a theoretical and empirical analysis of internal promotion versus external hiring, with predictions concerning the probability that a firm's manager departs for another firm when getting promoted.

us to consider both within-firm and across-firm job changes (and the resulting wage changes). Our results suggest that theoretical predictions concerning the signaling role of promotions are more strongly supported for within-firm promotions than for across-firm promotions.

Three recent papers provide empirical evidence related to this study. The first of these, DeVaro and Waldman (2012), is the most closely related to the present study. That analysis uses data on white males from the single, large American firm in the financial services industry that was studied in the classic internal labor market analyses by Baker, Gibbs, and Holmström (1994a,b). DeVaro and Waldman (2012) find that across all education groups, after controlling for worker performance the probability of promotion is increasing in the level of educational attainment, and this result is stronger for first promotions than for subsequent promotions. Furthermore, for first promotions the authors find that the wage increase due to promotion (measured as either a change in levels or a change in logs) is smaller for those with masters degrees than for those with bachelors degrees, whereas this relationship is not found for subsequent promotions. In contrast, they do not find the predicted relationships between education and wage growth for high school educated workers and those with Ph.D.s. Overall the results support signaling being important for workers with BA and MA degrees, whereas the evidence concerning the importance of signaling for high school graduates and Ph.D.s is mixed.[7]

[7] Belzil and Bognanno (2010) report related results in the context of a study of fast-track promotions using a panel of 30,000 American executives, though their data do not include time-varying, job-specific worker performance ratings to be used as controls.

Second, DeVaro, Ghosh, and Zoghi (2012) use data from the American firm analyzed in Gibbs and Hendricks (2004) to investigate four empirical predictions from a theoretical model that extends the Milgrom-Oster framework. As in Milgrom and Oster (1987), consider two groups of workers (Invisibles and Visibles) where the former consists of workers who are traditionally thought to be disadvantaged in the labor market (e.g. women or racial minorities) and the latter consists of workers who are traditionally thought to be advantaged (e.g. men or whites). Suppose that job hierarchies vary in the degree to which job tasks differ across hierarchical levels. DeVaro, Ghosh, and Zoghi (2012) show that four testable implications emerge. First, controlling for worker performance, promotion probabilities are lower for Invisibles than Visibles, and second, this difference is mitigated in job hierarchies that exhibit significant variability of tasks across job levels. Third, the wage growth attached to promotion is higher for Invisibles than Visibles, and fourth, this difference decreases when tasks become more variable across hierarchical levels. The authors conduct the empirical tests focusing on race, where Invisibles are nonwhite workers and Visibles are white workers. However, in principle the tests could also be applied in the case of gender. The empirical evidence supports the first three of these predictions, and the authors discuss some potential reasons for the lack of support of the fourth. Given that three of the four predictions are empirically supported the authors interpret the evidence as broadly suggestive of a signaling role of promotions.

Third, like the present study, Bognanno and Melero (2012) seek to empirically test the signaling role of promotions in panel data spanning many firms. They use the British Household Panel Survey (BHPS) to investigate whether promotions that reveal more information to the outside market (e.g. those for young workers or for workers with low education levels) are accompanied by greater percentage increases in the wage. Bognanno and Melero find results in accordance with their hypotheses regarding the effect of both age and education on the increase in log-wages attached to promotions, though the statistical significance of their estimates hinges on the definition of promotion. Apart from the fact that their paper covers Britain - whereas ours covers Finland and Germany - the focus of the two studies differs in a number of ways. For example, our chapter considers theoretical predictions concerning both promotion probability and wage increases conditional on promotion, whereas theirs only considers the latter; our chapter distinguishes between first promotions and subsequent promotions, following the theoretical predictions from DeVaro and Waldman (2012), whereas theirs does not; and their paper does not consider gender differences nor does it distinguish between within-firm to across-firm promotions, whereas these are important points of focus in our analysis.

All theoretical predictions in a promotion signaling framework, whether concerning promotion probabilities or the wage increases attached to promotion, include the qualifying phrase “holding worker performance constant”. As an example illustrating why this is so important, consider the theoretical prediction that promotion probability is increasing in the level of educational attainment. Absent a control for worker performance, an empirical finding that promotion probability is increasing in education would be no surprise. Workers with more education are, on average, more productive than those with less education. Thus, it should be expected that workers with more education are more likely to be promoted. The requirement that the worker's pre-promotion job performance be held constant poses a considerable challenge for empirical tests given that performance measurements are rarely available in the few data sets that contain all the other requisite information (e.g. promotions, wages, measures of job hierarchy, and educational attainment).

There are three potential approaches for dealing with the performance measurement problem. One approach is to rely on single-firm personnel data sets that often contain supervisor-reported worker performance measurements which are inherently job-specific and time varying. Such measures are typically unavailable in data sets spanning many firms, and even if they were available the comparability of the ratings across firms would be questionable (e.g. the ratings might be measured in different units and on different scales). Examples of the single-firm approach to solving the performance measurement problem are DeVaro and Waldman (2012) and DeVaro, Ghosh, and Zoghi (2012). However, this approach has three important limitations, all of which derive from the nature of the data. First, as noted in Baker and Holmström

(1995), it is unclear to what extent the results of single-firm case studies generalize to broader classes of employers. Second, workers who switch firms disappear from the sample, so there is no way to know whether they switched to a new firm, or to unemployment, and in the case of switching firms their new job level and wage are unobservable. Given that many workers come and go in the typical firm, particularly over a long time horizon, dropping all of the “leavers” from an analysis is problematic and could bias the results of an analysis of promotion and wage dynamics. Third, such data do not allow the researcher to investigate whether the signaling role of promotions differs between within-firm versus across-firm promotions. A second approach is to use large-scale, multi-firm panels that mitigate the limitations of single-firm studies, but at the expense of forgoing controls for worker performance. This is the approach taken in Bognanno and Melero (2012). A third and new approach, taken in the present chapter, is to exploit large-scale, worker-firm panel data while inferring a job-specific, time-varying worker performance measure by estimating the idiosyncratic component of individual performance bonuses. The approach of inferring a measure of individual performance from bonus data has been used before for different purposes in Pekkarinen and Vartiainen (2006) and Gittings (2012a,b). Since lack of crucial data on worker performance has prevented researchers from exploiting rich, large-scale, worker-firm panels to empirically test the predictions of theories concerning careers, our approach opens the door for future work in this literature to move beyond single-firm case studies. Our empirical tests are not subject to any of the aforementioned limitations of single-firm studies.

In the remainder of the chapter we devote two sections to the Finnish analysis and two to the German analysis before summarizing and concluding.

4.2 Data and Measures: Finland

The Finnish data are drawn from a large, worker-firm-linked panel. Our analysis is based on the years 2001 to 2010. The source of the annual survey data is the records of the Confederation of Finnish Industries (EK), which is the central organization of employer associations in Finland. EK-affiliated firms represent over two thirds of the Finnish GDP and over 90 percent of exports, so that the data represent a significant share of the Finnish economy.[8] The data are of high quality given that they are based on firms' administrative records, and since participation in the survey is compulsory except for the smallest firms, the response rate is nearly 100 percent. Our sample consists of 269,559 person-years, of which 33.4 percent represent women. The number of individual persons is 86,900, which includes 31,572 women. The data allow us to follow individual workers' careers over time, to distinguish within-firm from across-firm promotions and to incorporate a large set of controls for worker and firm characteristics.

[8]See Kauhanen and Napari (2012a) for a more detailed description of the data and of the wage-setting process in Finland, and see Asplund (2007) and Vartiainen (1998) for descriptions of the Finnish bargaining system.

Apart from the performance measurement problem discussed in the introduction, moving from single-firm data to multi-firm data poses a second empirical challenge. Defining promotions across firms is difficult because job hierarchies are not easily measured in a comparable way across firms.[9] This problem can be resolved in the Finnish data given that all firms use the same 56 job titles and four hierarchical levels, which makes the classification comparable across firms. We can therefore define a promotion as a transition across hierarchical levels (either within or across firms).

4.2.1 Variables and Data Selection: Finland

We restrict our analysis to all workers who appear in the data after 2001, since in this subsample we can distinguish more cleanly between workers receiving their first promotion and those receiving subsequent promotions.[10] The theoretical argument for making this distinction is given in DeVaro and Waldman (2012).[11]

We restrict attention to white-collar jobs in manufacturing because complexities in the occupational classification system for blue-collar jobs make it

[9]A small number of papers have addressed this issue. Frederiksen et al. (2010) use occupation codes to distinguish between executive and non-executive ranks, while Da Silva and Van der Klaauw (2011) use Portuguese matched employer-employee data that contain a hierarchy definition that is comparable across firms.

[10]This is because in 2001 there was a change in the way job titles were coded, and it is difficult to compare codes consistently before and after this change.

[11]Even in our "first-promotion subsample" it is possible that some workers were in fact promoted earlier. This could happen if, for example, the firm first appears in the data in 2002. In this case 2002 would be the first observation for a given worker, but that person might have been promoted in the firm at an earlier date.

difficult to allocate those jobs across hierarchical levels. We also restrict our analysis to full-time workers (defined as regular weekly working hours exceeding 30), though this restriction is of little practical consequence given that the share of part-time workers is small for white-collar jobs (about 2 percent in 2006).

The two dependent variables in this analysis are a binary indicator for whether a promotion was received and the annual wage change (measured in both levels and logs). We measure promotions based on changes in job titles. In manufacturing, these titles are comprised of two parts. The first is a three-digit code describing the field (e.g. R&D, production, sales and marketing), of which there are 56. The second describes the organizational level, and it has four categories. For the wage change analysis, following DeVaro and Waldman (2012), the annual wage change does not include bonuses. In our analysis, excluding bonuses from the construction of the dependent variable avoids an endogeneity problem, given that we use the bonus data to infer individual performance, which is a key control variable required by the theory.

The independent variable in this analysis is educational attainment. As discussed in DeVaro and Waldman (2012), given that a higher observed level of schooling serves as a signal that the worker belongs to a higher productivity group, in models of promotion probability and of the wage growth attached to promotion it is preferable to focus on the receipt of a degree rather than on years of education. For example, taking five years to complete a BA degree does not signal higher quality than taking four, and taking three years to complete an MBA does not signal higher quality than taking two. In the absence of direct measures of degree receipt, DeVaro and Waldman (2012) is forced to define their four education dummies for degrees indirectly (and possibly with error) based on years of education. An advantage of the Finnish data is that we directly observe five categories of education levels, which we aggregate to the following four educational groups (upper secondary, lowest-level tertiary, BA, and GRAD), where BA is lower-degree-level tertiary education and GRAD is higher-degree-level tertiary education or doctoral (or equivalent-level tertiary) education. We aggregate from five categories to four because of an extremely small sample size in the highest-level category.[12]

4.2.2 Worker Performance Measures: Finland

Data on time-varying, job-specific, individual worker performance measures are needed to test the promotion-as-signal hypothesis. Such data are absent in the Finnish data set, as in most other data sets that span many firms, including the British BHPS data used in Bognanno and Melero (2012). The difficulty of obtaining such performance data necessitated using personnel records from single-firm cases in DeVaro and Waldman (2012) and DeVaro, Ghosh, and

[12]Like the Finnish data, the British data used in Bognanno and Melero (2012) also contain direct measures of degree receipt. In that study the authors use those dummies to construct an inferred "years of education" measure on which they base their analysis, thereby assuming that the effect of an additional year of education on wage growth is the same, regardless of the education level.

Zoghi (2012). To overcome the problem in the present study, we infer measures of worker performance from the amount of performance-related-pay the worker received, following a similar approach to those used in Pekkarinen and Vartiainen (2006) and Gittings (2012a,b). About 58 percent of workers in the data received performance-related-pay.

We begin by estimating a regression in which the dependent variable is the amount of performance-related-pay that worker i receives in year $t+1$, and the independent variables (including job title dummies, job level dummies, year dummies, and industry dummies) are measured in year t. The reason for leading the dependent variable is that payments for performance in year t are typically paid in year $t+1$. We then use the residuals from the regression as measures of worker performance. Thus, each worker's performance is measured by how much performance-related-pay the worker received compared to other workers in the same job title, same job level, and same industry, in a given year.

A feature of actual (as opposed to inferred) worker performance ratings is that they tend to be positively autocorrelated, with the strength of the correlation diminishing with the order of the autocorrelation. This is the case, for example, in Table 10 of DeVaro and Waldman (2012), which reports the bivariate correlation matrix of the workers' actual annual performance ratings and their first three lagged values, using data from a single American firm in the financial services industry. That table is reproduced in Panel A of Table 4.1

Table 4.1: Autocorrelation Matrix for Worker Performance

Panel A: Actual Performance Ratings in One American Firm

	Performance	Performance$_{t-1}$	Performance$_{t-2}$	Performance$_{t-3}$
Performance	1.000			
Performance$_{t-1}$	0.581*	1.000		
Performance$_{t-2}$	0.394*	0.590*	1.000	
Performance$_{t-3}$	0.249*	0.398*	0.610*	1.000

Panel B: Inferred Performance Ratings in Finnish Panel Data

	Performance	Performance$_{t-1}$	Performance$_{t-2}$	Performance$_{t-3}$
Performance	1.000			
Performance$_{t-1}$	0.518*	1.000		
Performance$_{t-2}$	0.382*	0.518*	1.000	
Performance$_{t-3}$	0.296*	0.381*	0.509*	1.000

Panel C: Inferred Performance Ratings in German Panel Data

	Performance	Performance$_{t-1}$	Performance$_{t-2}$	Performance$_{t-3}$
Performance	1.000			
Performance$_{t-1}$	0.644*	1.000		
Performance$_{t-2}$	0.565*	0.619*	1.000	
Performance$_{t-3}$	0.497*	0.547*	0.606*	1.000

Sources: Panel A: DeVaro and Waldman (2012), Table 10, based on single-firm personnel data from Baker, Gibbs, and Holmström (1994a,b); Panel B: Finnish EK data, 2002-2010; Panel C: German SOEP, 1984-2009.
* Statistically significant at the 1% level.

in the present chapter. As shown in Panel B of that table, we find exactly the same pattern in the Finnish data, using the performance measure we inferred from bonus data. The correlation matrix is strikingly similar to that of the DeVaro-Waldman analysis.

A potential issue that arises in the case of workers who change firms is that performance related pay is typically paid in year $t + 1$ based on performance in year t. This could lead us to understate the performance of workers who change firms, because a worker who changes firms in period $t + 1$ might not receive performance related pay in that year. This issue does not pose a problem for our analysis given that the estimation results in the following section are insensitive to the exclusion of workers who changed firms and received zero performance related pay. Another potential concern is that a particular residual from the performance regression might have a high value because of an unobserved characteristic of the firm rather than because of high worker performance. To address this possibility, as a robustness check we estimated the performance-related-pay regression including firm fixed effects. When the performance measure is constructed using this regression, our results of interest are virtually identical to those we report in this study.[13]

4.3 Empirical Analysis: Finland

The following two subsections present the analyses of promotion probability and the wage change conditional on promotion, respectively.[14] Descriptive statistics for all variables in the subsequent analysis appear in Table 4.2.

4.3.1 Promotion Probability: Finland

We estimate a multinomial probit model with a trivariate dependent variable in which the baseline outcome, 0, is no promotion, outcome 1 is promotion

[13] This robustness check in which firm fixed effects are included in the performance-related-pay regression is not possible in the German analysis described later, given that in the GSOEP data the worker cannot be linked to the firm.

[14] Our approach is similar to that used in DeVaro and Waldman (2012), and we refer readers to that study for more detailed discussions of the underlying theoretical motivation for the empirical models we estimate.

Table 4.2: Descriptive Statistics, Finland

	All Workers		Men Only		Women Only	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
Female	0.337	0.473				
Promotion	0.067	0.250	0.066	0.249	0.068	0.252
Firm change	0.042	0.201	0.043	0.202	0.042	0.200
Demographics						
Upper secondary	0.301	0.458	0.312	0.463	0.278	0.448
Lowest level tertiary	0.111	0.315	0.093	0.290	0.148	0.355
BA	0.348	0.476	0.359	0.480	0.326	0.469
GRAD	0.240	0.427	0.236	0.425	0.247	0.431
Age	33.994	7.894	34.052	7.810	33.879	8.055
Tenure	2.119	2.056	2.168	2.086	2.021	1.995
Occupation						
Hourly wage	17.866	5.729	18.630	5.749	16.369	5.382
Management	0.032	0.176	0.037	0.188	0.022	0.148
Professional	0.213	0.409	0.240	0.427	0.158	0.365
Expert	0.550	0.498	0.595	0.491	0.460	0.498
Clerical	0.206	0.404	0.127	0.333	0.360	0.480
Firm Size						
0-50	0.106	0.308	0.107	0.309	0.106	0.307
51-100	0.083	0.275	0.078	0.268	0.091	0.288
101-200	0.125	0.331	0.122	0.327	0.130	0.337
201-500	0.199	0.400	0.198	0.398	0.203	0.402
501-1000	0.115	0.319	0.127	0.332	0.093	0.290
1001-2000	0.092	0.289	0.083	0.276	0.110	0.312
2000+	0.280	0.449	0.286	0.452	0.268	0.443
Observations	269,559		178,728		90,831	

Source: Finnish EK data, 2002-2010.

within the firm, and outcome 2 is promotion across firms. The dependent variable refers to the outcome for worker i in year t, whereas all right-hand-side variables are measured in year $t-1$. The independent variables of interest are the dummies for educational attainment. The control variables include worker performance (as defined in the preceding section), age, age squared, job tenure (in years) at the firm, job tenure (in years) at the firm squared, job level dummies, and job title dummies.

Table 4.3 displays average marginal effects, where the omitted educational group is BA, which is the second highest of the four groups. The table reveals that the overall probability of within-firm promotion for all workers combined is 6.2 percent. The probability of a within-firm first promotion is a bit higher, at 6.6 percent, whereas the probability of a within-firm subsequent promotion (conditional on having received an earlier promotion) is 3.8 percent. The probability of across-firm promotion is extremely small in the white-collar Finnish manufacturing data, at less than 1 percent. Although most promotions in the Finnish data occur within firms, the sample size is large enough to support analysis of across-firm promotions. Six interesting results emerge from Panel A, which combines men and women.

First, as seen in column 1, the probability of within-firm promotion is increasing in the level of educational attainment, holding worker performance constant. This is the same result found in DeVaro and Waldman (2012) which considers only white, male stayers and within-firm promotions in a single firm.

Second, the incremental effects of the education variables are smaller in column 5 than in column 3. This suggests that the first result is stronger for within-firm first promotions than for within-firm subsequent promotions, as theory predicts. This result also matches what was found in DeVaro and Waldman (2012), which provides the following theoretical rationale. As other employers in the labor market learn more about a worker's abilities (as a consequence of observing the promotion record) education carries less informational content, and its importance diminishes. We suspect that our evidence in favor of this second result, here and throughout the chapter, is understated given

Table 4.3: Multinomial Probit, Promotion Within and Across Firms, Finland

Panel A: All Workers

	All Workers		First Promotion		Subsequent Promotion	
	(1) Within	(2) Across	(3) Within	(4) Across	(5) Within	(6) Across
Upper secondary	-0.011***	-0.002***	-0.013***	-0.002***	-0.002	-0.001
	(-6.28)	(-3.23)	(-6.40)	(-3.08)	(-0.54)	(-0.48)
Lowest level tertiary	-0.014***	-0.001	-0.016***	-0.002*	-0.001	0.003
	(-4.78)	(-1.35)	(-5.20)	(-1.76)	(-0.12)	(1.18)
GRAD	0.036***	0.005***	0.037***	0.005***	0.024***	0.004***
	(19.67)	(7.88)	(17.63)	(7.52)	(6.51)	(2.99)
Performance t-1	0.007***	-0.004***	0.007***	-0.004***	0.006***	-0.002***
	(14.41)	(-12.36)	(13.41)	(-11.28)	(8.35)	(-4.01)
Female	-0.022***	-0.002***	-0.026***	-0.003***	-0.002	-0.001
	(-12.94)	(-4.05)	(-13.27)	(-4.38)	(-0.69)	(-0.46)
Pr(Y=k)	0.062	0.006	0.066	0.007	0.038	0.005
Observations	118,984	118,984	101,502	101,502	17,482	17,482

Panel B: Men

	All Workers		First Promotion		Subsequent Promotion	
	(1) Within	(2) Across	(3) Within	(4) Across	(5) Within	(6) Across
Upper secondary	-0.014***	-0.003***	-0.016***	-0.003***	0.000	-0.001
	(-6.33)	(-3.48)	(-6.63)	(-3.19)	(0.05)	(-0.85)
Lowest level tertiary	-0.012***	-0.002	-0.014***	-0.002	0.002	0.001
	(-3.23)	(-1.48)	(-3.58)	(-1.58)	(0.27)	(0.45)
GRAD	0.031***	0.005***	0.032***	0.005***	0.018***	0.004***
	(14.39)	(6.19)	(12.93)	(5.94)	(4.17)	(2.87)
Performance t-1	0.006***	-0.004***	0.006***	-0.005***	0.005***	-0.002***
	(11.93)	(-10.84)	(11.27)	(-9.92)	(6.79)	(-4.16)
Pr(Y=k)	0.061	0.006	0.066	0.007	0.034	0.004
Observations	81,776	81,776	69,472	69,472	12,304	12,304

Panel C: Women

	All Workers		First Promotion		Subsequent Promotion	
	(1) Within	(2) Across	(3) Within	(4) Across	(5) Within	(6) Across
Upper secondary	-0.009***	-0.000	-0.009**	-0.001	-0.012	0.002
	(-2.75)	(-0.41)	(-2.43)	(-0.46)	(-1.43)	(0.82)
Lowest level tertiary	-0.013***	-0.000	-0.016***	-0.001	-0.003	0.005
	(-2.89)	(-0.10)	(-3.10)	(-0.51)	(-0.30)	(1.14)
GRAD	0.041***	0.005***	0.040***	0.005***	0.034***	0.004
	(11.88)	(4.49)	(10.16)	(4.30)	(4.69)	(1.63)

Performance t-1	0.011***	-0.003***	0.011***	-0.003***	0.013***	-0.003***
	(11.88)	(-6.11)	(11.95)	(-5.53)	(8.03)	(-2.97)
Pr(Y=k)	0.063	0.006	0.066	0.006	0.047	0.006
Observations	37,208	37,208	32,030	32,030	5,178	5,178

Notes: Cell entries are average marginal effects from a multinomial probit, with t-statistics in parentheses. Base Outcome 0: no promotion; Outcome 1: promotion within firm ("Within"); Outcome 2: promotion across firms ("Across"). Row "Pr(Y=k)" refers to the probability of the column's outcome. Base education category is the second-highest education level, BA. All right-hand-side variables are measured in year t-1, and the dependent variable is measured in year t. All specifications include age, (age) squared, job tenure at the firm, (job tenure at the firm) squared, job level dummies, job title dummies, and an intercept term. Source: Finnish EK data, 2002-2010.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

that our method of distinguishing between first and subsequent promotions likely produces some misclassifications that would blur the distinction between columns 3 and 5.

Third, as seen in column 2, the result that promotion probability is increasing in the level of educational attainment (controlling for pre-promotion performance) also holds in the rare case of across-firm promotions just as it did for within-firm promotions.

Fourth, as seen by comparing the incremental effects of education in column 4 to those in column 6, the result that the across-firm promotion probability is increasing in the level of educational attainment is stronger for first promotions than for subsequent promotions. These third and fourth results concerning across-firm promotions parallel those that are found, theoretically and empirically, in DeVaro and Waldman (2012) for within-firm promotions. The result that these patterns of evidence are also true for across-firm promotions is new to the literature.

Fifth, as seen in columns 1, 3, and 5 concerning within-firm promotions, the marginal effect of pre-promotion performance has the anticipated positive sign. However, as seen in columns 2, 4, and 6, the sign flips to negative in the rare event of across-firm promotions. One possible explanation for the negative sign is adverse selection in the labor market as discussed in Greenwald (1986). However, we see that explanation as unlikely given that, as we show in Table 4.4, across-firm moves (whether promotions or not) are on average accompanied by large wage increases. We think that a more likely explanation for the negative sign derives from the definition of our performance measure, which is inferred from individual bonus data. Low measured performance in the pre-promotion year means the worker's bonus was low, and in such cases the worker may be more open to advancing the career at a different firm, whereas if last year's bonus was extremely high the worker might find it hard to leave.

Sixth, the probability of promotion (within and across firms) is lower for women than men. The lower promotion probability for women in this data set is documented in Kauhanen and Napari (2012b). However, like most studies in the literature, that study does not control for pre-promotion, job-specific worker performance. As noted earlier, one study that controls for such pre-promotion job performance (measured as the supervisor's subjective rating on a 0-100 scale) is Blau and DeVaro (2007), which also finds evidence of lower within-firm promotion probabilities for women than men, for recent hires in an American establishment-level cross section. In that study, the magnitude of the marginal effect of gender is in the neighborhood of 2 to 3 percentage points, depending on the specification, just as it is in columns 1 and 3. When a prior promotion has occurred, there is no evidence in the Finnish data that the likelihood of a future promotion (within or across firms) is different for women versus men. This is consistent with the argument developed in Milgrom and Oster (1987) based on the Invisibility Hypothesis. At earlier career stages before a first promotion has been received, the labor market finds it harder to learn the abilities of (Invisible) women than (Visible) men. However, when a promotion occurs a considerable amount of information is revealed to the market concerning worker ability, so the visibility of women improves relative to men, explaining why the gender difference diminishes for the probability of subsequent promotion.

Panels B and C of Table 3 repeat the preceding analyses for the subsamples of men and women, respectively. The first five results just stated largely hold for both men and women, with few noteworthy differences between these two subsamples. All of the preceding results are insensitive to controlling for an additional lag of worker performance.

4.3.2 Wage Growth and Promotion: Finland

The promotion-as-signal hypothesis implies that the wage increase that accompanies a promotion should decrease with the level of educational attainment, controlling for pre-promotion performance. The intuition is that when highly-educated workers are promoted, employers are unsurprised since they already viewed these workers as being highly capable. There is therefore less positive updating in beliefs about the abilities of promoted workers, and consequently less of an increase in the wage competing employers are willing to offer. This in turn means that the worker's original employer need not offer a large wage increase to retain the worker. A further prediction of the theory is that the result just noted should be stronger for first promotions than subsequent promotions. Theoretical predictions involving wage growth in this literature are more often stated in wage levels than in log-wages. We consider both in this chapter, as in DeVaro and Waldman (2012).[15]

We analyze the relationship between educational attainment and the wage increase that accompanies promotion by constructing four dummies capturing within-firm promotions, across-firm promotions, within-firm non-promotions, and across-firm non-promotions. In OLS regressions for each of two dependent variables (annual change in wage level, and annual change in log-wage), we include three of the preceding four dummies (excluding the indicator for within-firm non-promotions) as main effects and also interacted with each of the education dummies. Our use of OLS regressions is consistent with the approach of DeVaro and Waldman (2012). Bognanno and Melero (2012) take an alternative approach that accounts for individual worker heterogeneity via random effects (or fixed effects in their models that include worker age but exclude years of education). Given that those authors are unable to control

[15]As noted in the introduction, Bognanno and Melero (2012) also test this empirical prediction and find supporting evidence for it depending on how promotions are defined. However, they only consider differences in log wages, they do not control for pre-promotion worker performance, and they do not distinguish first promotions from subsequent promotions.

for pre-promotion performance, their decision to incorporate individual effects into the analysis is well advised. Note that most of the unobserved worker characteristics (some time varying, others not) that researchers are worried about in a wage growth model relate to and ultimately predict worker performance. Examples include worker attitudes, levels of motivation, effort levels, unobserved components of ability, unmeasured mental and physical health, etc. These unobserved factors affect wages via their effect on job performance, so most unobserved factors that one would be interested in absorbing via individual effects are already subsumed in measures of worker performance. These worker performance controls are included in our analysis as they are in DeVaro and Waldman (2012). Nonetheless, as a robustness check we also estimated our models accounting for individual worker heterogeneity via random effects and found results very similar to those we report here, which again is unsurprising given that the main unobserved components one hopes to absorb in an individual effect should already be embedded in our control for worker performance. Note that in random effects and fixed effects models the individual effect cannot be interpreted as fully accounting for worker performance, because some important determinants of worker performance tend to be time-varying (e.g. worker effort).

Table 4.4 displays the results for men and women combined (Panel A), men (Panel B), and women (Panel C). Several points are worth highlighting.

First, as seen in columns 1 and 4 of Panel A, whether considering changes

Table 4.4: OLS Estimates, Changes in Wage Levels and Log-Wage, Finland

Panel A: All Workers

	Wage Levels			Log-Wages		
	(1) All Workers	(2) First Promotion	(3) Subsequent Promotion	(4) All Workers	(5) First Promotion	(6) Subsequent Promotion
Upper secondary	0.081***	0.075***	0.087***	0.007***	0.007***	0.005***
	(8.16)	(7.10)	(3.07)	(10.72)	(9.73)	(3.51)
Lowest level tertiary	0.008	0.003	0.030	0.002***	0.002**	0.003
	(0.60)	(0.23)	(0.72)	(2.74)	(2.48)	(1.13)
GRAD	0.128***	0.135***	0.113***	0.003***	0.003***	0.003**
	(12.26)	(11.60)	(4.83)	(5.47)	(5.41)	(2.54)
Promotion-Within	0.623***	0.600***	0.867***	0.034***	0.033***	0.042***
	(15.25)	(13.49)	(10.00)	(16.72)	(15.17)	(9.19)
× Upper Secondary	0.150**	0.174***	-0.030	0.009***	0.011***	-0.004
	(2.45)	(2.72)	(-0.17)	(2.63)	(2.83)	(-0.44)
× Lowest level tertiary	0.045	0.086	-0.390	0.001	0.005	-0.049
	(0.45)	(0.83)	(-0.87)	(0.16)	(0.98)	(-1.16)
× GRAD	0.141**	0.132**	0.209	0.001	0.001	0.003
	(2.32)	(1.99)	(1.45)	(0.35)	(0.24)	(0.41)
Promotion-Across	1.603***	1.564***	1.833***	0.085***	0.085***	0.089***
	(10.59)	(9.65)	(4.41)	(10.22)	(9.40)	(4.06)
× Upper Secondary	0.215	0.286	-0.507	0.016	0.018	-0.017
	(0.90)	(1.14)	(-0.63)	(1.14)	(1.25)	(-0.43)
× Lowest level tertiary	-0.746**	-0.853**	0.304	-0.039**	-0.044**	0.005
	(-2.27)	(-2.42)	(0.33)	(-2.16)	(-2.23)	(0.11)
× GRAD	0.883***	0.882***	0.938	0.025**	0.024*	0.035
	(3.55)	(3.27)	(1.51)	(2.12)	(1.88)	(1.14)
No Promotion-Across	0.698***	0.679***	0.745***	0.038***	0.038***	0.036***
	(10.77)	(9.04)	(6.05)	(12.14)	(10.60)	(5.57)
× Upper Secondary	0.041	0.034	0.110	0.005	0.005	0.006
	(0.45)	(0.34)	(0.55)	(1.08)	(0.95)	(0.54)
× Lowest level tertiary	-0.197	-0.149	-0.499	-0.011*	-0.010	-0.018
	(-1.38)	(-0.95)	(-1.48)	(-1.69)	(-1.42)	(-1.11)
× GRAD	0.031	0.025	0.054	-0.004	-0.004	-0.002
	(0.32)	(0.23)	(0.26)	(-0.95)	(-0.91)	(-0.22)
Performance t-1	0.010***	0.009***	0.015***	-0.000**	-0.000**	-0.000
	(4.40)	(3.72)	(2.61)	(-2.54)	(-2.26)	(-0.77)
Female	-0.091***	-0.097***	-0.064***	-0.003***	-0.003***	-0.001
	(-10.18)	(-9.88)	(-2.88)	(-4.69)	(-4.64)	(-1.14)
Observations	122,152	103,317	18,835	122,150	103,315	18,835
R^2	0.061	0.060	0.083	0.058	0.058	0.078

Panel B: Men

	Wage Levels			Log-Wages		
	(1) All Workers	(2) First Promotion	(3) Subsequent Promotion	(4) All Workers	(5) First Promotion	(6) Subsequent Promotion
Upper secondary	0.085***	0.077***	0.097***	0.007***	0.007***	0.007***
	(6.96)	(5.90)	(2.87)	(9.45)	(8.29)	(3.57)
Lowest level tertiary	-0.001	0.001	-0.014	0.002	0.002	0.002
	(-0.06)	(0.03)	(-0.25)	(1.58)	(1.61)	(0.44)
GRAD	0.127***	0.129***	0.133***	0.003***	0.003***	0.003***
	(9.96)	(8.96)	(4.74)	(4.49)	(3.97)	(2.79)
Promotion-Within	0.606***	0.582***	0.898***	0.032***	0.031***	0.043***
	(11.88)	(10.52)	(8.25)	(12.67)	(11.46)	(7.66)
× Upper Secondary	0.146**	0.172**	-0.025	0.009**	0.010**	-0.003
	(1.97)	(2.21)	(-0.12)	(1.96)	(2.17)	(-0.28)
× Lowest level tertiary	0.010	0.102	-1.183	-0.002	0.006	-0.111
	(0.07)	(0.67)	(-1.49)	(-0.20)	(0.77)	(-1.25)
× GRAD	0.136*	0.124	0.279	0.001	0.001	0.004
	(1.74)	(1.46)	(1.59)	(0.31)	(0.22)	(0.56)
Promotion-Across	1.757***	1.813***	1.381***	0.094***	0.098***	0.067***
	(10.68)	(9.93)	(4.28)	(10.35)	(9.68)	(4.17)
× Upper Secondary	0.304	0.281	0.282	0.020	0.018	0.022
	(1.09)	(0.96)	(0.30)	(1.28)	(1.07)	(0.50)
× Lowest level tertiary	-0.835*	-0.908*	-0.071	-0.046*	-0.051*	-0.001
	(-1.83)	(-1.86)	(-0.17)	(-1.80)	(-1.87)	(-0.05)
× GRAD	0.732**	0.665**	1.221*	0.017	0.013	0.047
	(2.46)	(2.03)	(1.93)	(1.21)	(0.83)	(1.57)
No Promotion-Across	0.771***	0.753***	0.825***	0.042***	0.042***	0.040***
	(9.16)	(7.65)	(5.65)	(10.60)	(9.14)	(5.42)
× Upper Secondary	0.047	0.054	0.025	0.005	0.006	-0.001
	(0.41)	(0.42)	(0.11)	(0.88)	(0.92)	(-0.07)
× Lowest level tertiary	-0.286	-0.222	-0.753	-0.015	-0.012	-0.033
	(-1.48)	(-1.07)	(-1.39)	(-1.63)	(-1.30)	(-1.29)
× GRAD	-0.010	0.020	-0.125	-0.007	-0.006	-0.010
	(-0.08)	(0.15)	(-0.49)	(-1.36)	(-1.03)	(-0.92)
Performance t-1	0.007***	0.007***	0.007	-0.000***	-0.000**	-0.001*
	(2.89)	(2.68)	(0.97)	(-2.59)	(-2.03)	(-1.91)
Observations	84,282	70,926	13,356	84,280	70,924	13,356
R^2	0.059	0.058	0.081	0.060	0.060	0.078

Panel C: Women

	Wage Levels			Log-Wages		
	(1) All Workers	(2) First Promotion	(3) Subsequent Promotion	(4) All	(5) First Promotion	(6) Subsequent Promotion
Upper secondary	0.062***	0.059***	0.080	0.006***	0.006***	0.003
	(3.76)	(3.42)	(1.54)	(4.88)	(4.80)	(1.16)

Lowest level tertiary	0.009	-0.006	0.087	0.002*	0.002	0.004
	(0.45)	(-0.32)	(1.47)	(1.79)	(1.40)	(1.23)
GRAD	0.109***	0.128***	0.051	0.002**	0.003***	0.000
	(6.08)	(6.43)	(1.19)	(2.33)	(2.97)	(0.16)
Promotion-Within	0.639***	0.617***	0.804***	0.037***	0.037***	0.040***
	(9.35)	(8.20)	(5.50)	(10.62)	(9.65)	(5.00)
× Upper Secondary	0.162	0.189*	-0.007	0.012*	0.013**	-0.003
	(1.53)	(1.68)	(-0.02)	(1.96)	(2.04)	(-0.24)
× Lowest level tertiary	0.085	0.063	0.150	0.004	0.004	-0.002
	(0.64)	(0.45)	(0.31)	(0.52)	(0.48)	(-0.09)
× GRAD	0.157*	0.154	0.115	0.001	0.001	0.001
	(1.66)	(1.51)	(0.46)	(0.25)	(0.17)	(0.04)
Promotion-Across	1.167***	0.861***	2.835**	0.061***	0.047***	0.136**
	(3.49)	(2.64)	(2.54)	(3.32)	(2.58)	(2.28)
× Upper Secondary	0.096	0.431	-2.095	0.010	0.026	-0.095
	(0.21)	(0.94)	(-1.39)	(0.38)	(0.91)	(-1.20)
× Lowest level tertiary	-0.406	-0.461	-0.271	-0.018	-0.017	-0.029
	(-0.81)	(-0.93)	(-0.17)	(-0.65)	(-0.59)	(-0.37)
× GRAD	1.336***	1.525***	0.352	0.049**	0.057**	0.011
	(2.92)	(3.28)	(0.25)	(2.12)	(2.42)	(0.15)
No Promotion-Across	0.499***	0.473***	0.567**	0.027***	0.027***	0.026**
	(5.88)	(5.34)	(2.46)	(5.83)	(5.46)	(2.10)
× Upper Secondary	0.003	-0.037	0.298	0.005	0.002	0.020
	(0.02)	(-0.26)	(0.76)	(0.54)	(0.22)	(0.83)
× Lowest level tertiary	0.035	0.070	-0.144	-0.001	-0.002	0.001
	(0.18)	(0.32)	(-0.45)	(-0.15)	(-0.18)	(0.06)
× GRAD	0.168	0.092	0.444	0.005	0.002	0.015
	(1.01)	(0.51)	(1.13)	(0.60)	(0.24)	(0.83)
Performance t-1	0.021***	0.018***	0.042***	0.000	-0.000	0.001***
	(4.89)	(3.75)	(4.30)	(0.58)	(-0.23)	(3.20)
Observations	37,870	32,391	5,479	37,870	32,391	5,479
R^2	0.075	0.074	0.121	0.060	0.059	0.108

Notes: Dependent variables are change in: 1) hourly wage levels (columns 1-3); and 2) hourly log-wages (columns 4-6), 2009 Euros. All right-hand-side variables are measured in year t-1, and the dependent variable is measured in year t. Base education category is the second-highest education level, BA. All specifications include age, (age) squared, job tenure at the firm, (job tenure at the firm) squared, job level dummies, job title dummies, and an intercept term. t-statistics are shown in parentheses. Source: Finnish EK data, 2002-2010.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

in wage levels or changes in log wages, in the case of within-firm promotions (which comprise the vast majority of all promotions) the results are consistent with the theoretical prediction for the lowest-level education group. That is, the coefficient of the interaction between the within-firm promotion dummy and the lowest-level education dummy is positive and statistically significant. For the case of the highest-level education group, the coefficient on the interaction term has the wrong theoretical sign but is statistically significant only in the case of wage levels. The fact that the prediction fails to hold for the highest-level educational group is also true in the case of white men in the firm analyzed in DeVaro and Waldman (2012).

Second, as seen in columns 2, 3, 5, and 6 of Panel A, the evidence of promotion signaling for the lowest-level education group is stronger for first promotions than for subsequent promotions, consistent with theory.

Third, for the rare cases of across-firm promotions the theoretical prediction concerning wage growth fails to hold in Panel A, and distinguishing first from subsequent promotions does nothing to change matters.

Fourth, comparing Panels B and C reveals that both in level and logs, for all workers and for first promotions, within-firm promotions are associated with larger wage increases for women than men, though the reverse is true for subsequent promotions. However, none of these gender differences are statistically significant at conventional levels. For across-firm moves (whether promotions or not), both in levels and in logs, wage increases from first promotion are higher for men than women (a difference that is statistically significant at conventional levels), but there is no statistically significant gender difference in the wage increases attached to subsequent promotions.[16] The Milgrom-Oster

[16]Kauhanen and Napari (2012b) also find that wage increases from across-firm promotions are higher for men than women but they do not separate first and subsequent promotions, nor

framework offers a potential explanation for the fact that across-firm job transitions are associated with larger annual wage increases for men than women, whereas there is no gender difference in the wage changes attached to within-firm promotion. More precisely, whatever mechanisms might be causing annual wage increases to be higher for men than women are weakened in the case of within-firm promotions for the following reason. Since promotions of (Invisible) women are more of a surprise to competing firms than promotions of (Visible) men, there is a larger positive update in the beliefs about womens' ability, and hence a larger wage increase attached to promotion. In fact, although the gender differences are statistically insignificant, the point estimates reveal a large wage increase for women than men for within-firm promotion, and this difference is even larger for first promotions and absent for subsequent promotions. This pattern of evidence is consistent with a potential signaling role of promotions that is stronger for women than men.

Finally, as has been well documented in the literature, Panel A reveals that within-firm promotions are associated with wage increases. If the promotion involves a change in firms, this wage increase is even larger. Even job transitions that occur across firms but that do not involve promotion are associated with big wage increases, relative to remaining in the original firm without a promotion. Across all models in wage levels, unsurprisingly, last year's performance is positively related to annual wage increases. In contrast, last year's

do they control for performance.

performance has essentially no effect in the models in logs.

The patterns of results in Panel B (for men) and Panel C (for women) essentially mirror those for Panel A.

4.4 Data and Measures: Germany

The German Socio-Economic Panel (GSOEP) is an annual panel survey of German households. The survey began in 1984, and as of 2012 there have been seven new waves added to the initial sample, including an East German sample starting in 1990. In addition to household information the panel contains a personal survey component which includes many employment-related questions. The data permit a definition of hierarchy and promotion that is consistent across firms. Workers are asked their occupational status, which can be interpreted as their hierarchical rank within the firm.[17] We describe the hierarchical assignment procedure in more detail in the Appendix B.1. Using the response to the question about occupational status, we allocate workers to one of four hierarchical levels: Lower, Middle, Upper and Executive.

As noted earlier, defining promotions consistently across firms poses a potential challenge in data sets spanning many firms. In the German data we measure promotions by a worker-reported survey indicator that a promotion

[17] Lluis (2005) and Cassidy (2012a) also use this GSOEP question for this purpose. See Appendix B.1 for an example of this question in the 1985 survey year.

has occurred. This type of measure resolves the issue of defining an across-firm promotion since the definition does not hinge on a particular definition of the job hierarchy. Furthermore, since this survey question is asked independently of the worker's occupation, we need not rely on occupation codes to define the hierarchy as has been done in previous work.[18] The disadvantage of using transitions across occupation codes to define promotions is that promotions more commonly occur within occupations than across occupations.[19]

4.4.1 Variables and Data Selection: Germany

Our analysis focuses on full-time workers between the ages of 20 and 65.[20] We focus only on white-collar, blue-collar, and civil service workers, dropping self-employed workers and apprentices. These selection criteria result in a total of 112,412 observations for which we can assign a worker to a job level. We drop observations for which wages are below 4800 Euros a year,[21] as well as outlying yearly bonuses of over 50,000 Euros. We also drop absolute net yearly wage changes between years that exceed 24,000 Euros per year. In total, we

[18]See, for example, Frederiksen, Halliday and Koch (2010), which uses occupation codes to group workers into executive and non-executive ranks, so that a promotion or demotion necessarily requires a change in occupation.

[19]For example, in the National Longitudinal Survey of Youth (NLSY), Cassidy (2012b) finds that roughly 60 percent of promotions occur within occupations. Furthermore, in the single-firm personnel data analyzed in DeVaro, Ghosh, and Zoghi (2012), the fraction of promotions occurring within-occupation is 93 percent using two-digit occupation codes and 92 percent using three-digit occupation codes.

[20]We identify full-time workers using the GSOEP-generated Labor Force Status variable and further restrict our attention to workers employed for over 30 hours per week on average.

[21]Income is denominated in 2009 Euros. We use net yearly labor income, as opposed to gross income.

lose 1168 observations due to wage or bonus data cleaning. Missing occupation, industry, and firm size data further reduce our sample by 5560. We lose 499 observations due to missing education, tenure, and experience data. Since a worker in the highest job level cannot be promoted, we exclude 5437 observations where the worker is in the Executive level in the initial period.

We define a promotion to occur when a worker's job level increases from one year to the next. Following DeVaro and Waldman (2012), we do not distinguish between single-level versus multiple-level promotions, e.g. from Lower to Middle versus from Lower to Upper (bypassing the Middle level). The self-reported nature of the worker's job level introduces the possibility of spurious level changes. To mitigate this problem, Lluis (2005) uses a job change question in conjunction with level change and wage change to determine promotions and demotions; in that study, a promotion occurs if: a) the worker reports both a job change and a level increase; or b) the worker reports only a level increase, but with a wage gain of at least 5%. Demotions are analogously defined, but in case (b), occur only for workers whose real wage decreases. Using endogenous wage information to determine level changes would be problematic for our analysis since we use wage changes as a dependent variable. For this reason, we clean the data by assuming that if a worker changes level between period 1 and period 2, but returns to the initial level in period 3, the level change was mismeasured. In this case, we assign the period 1 (and period 3) level to period 2. This approach is similar to the method used in Yamaguchi (2010) for occupation codes, but where the intervening period is a single year, instead of the worker's entire firm tenure.[22] Our correction procedure reduces the yearly promotion rate from 10.7% to 5.7%.[23]

We define a categorical variable based on the worker's number of years of education, labeling respondents with fewer than 13 years of schooling as having a high school degree or less (HS), those with 13 to 16 years as having a bachelor's degree (BA), and those with 17 years or more as having a graduate degree (GRAD).[24] Testing the DeVaro and Waldman (2012) model requires a ranking of education corresponding to increasing average ability. However, it is unclear how that ranking should be constructed in Germany due to the large number of different degree types, hence we rely instead on years of schooling. Firm size appears in the survey as a categorical variable with the following four size groups: 1-19, 20-199, 200-1999 and 2000+ workers. Industry classification is at the two-digit level, following the NACE classification system, and occupation classification uses the three-digit ISCO-88 system. Job tenure and worker experience are both worker-reported, where only full-time experience is used.[25]

[22]In that study, if a worker changes occupations but eventually changes back to the original occupation while at the same firm, Yamaguchi assumes that the intervening spell was mismeasured and imposes the original occupation code for the intervening period.

[23]Although this procedure probably mislabels some genuine promotions, the average wage change experienced by promoted workers increases from 3.7% to 4.6% after we impose the correction. For workers who are promoted based on the non-corrected procedure but not promoted after the correction, average wage change is only 2.6%. This is suggestive that many corrected "promotions" are, in fact, spurious.

[24]This approach of inferring indicators for levels of educational attainment from data on years of education was taken in DeVaro and Waldman (2012).

[25]Ignoring part-time experience is unlikely to be a problem, given that the mean part-time

We partition the sample into first-promotion and subsequent-promotion subsamples, where the first-promotion subsample includes workers who have either not yet received a promotion, or who have just received their first promotion in that year.[26] All other observations are included in the subsequent-promotion sample. We note that in some cases our approach might misclassify a subsequent promotion as a first promotion. This issue arises because in the GSOEP, since many of the workers in the survey are only observed starting from a later age,[27] we do not observe the early part of the labor market history for many workers. Thus, for some workers in the survey the first promotion received may not be their true first promotion.[28]

4.4.2 Worker Performance Measurement: Germany

As in our Finnish analysis, we infer a measure of individual, job-specific performance from data on individual performance bonuses. The GSOEP asks workers for the amount of the bonus received in the previous year, divided into Christmas, vacation, profit sharing and "other" bonus. We aggregate all four types into a single bonus amount (setting missing bonus data to zero for each

and full-time experience are roughly 2 years and 15 years, respectively.

[26] In our sample, 78% of promotions are "first" promotions.

[27] The mean worker is first observed in the sample at age 33.

[28] A similar concern pertains to DeVaro and Waldman (2012). In that analysis, the single-firm personnel records did not capture the entire hierarchy of the firm but rather only the managerial portion of it. So when a worker first appears in that sample, it is impossible to know whether the worker entered from outside the firm or was promoted up from the non-managerial ranks of the firm. In the latter case, a worker who appears to be promoted for the first time (in the sample) would in fact have experienced earlier promotions in the firm, unbeknownst to the researcher.

type) and use this to impute performance.[29] A large fraction (75%) of workers received a bonus, and the average annual bonus amount is 1470 Euros.

The imputation procedure for the GSOEP is similar to the procedure used for the Finnish data. We measure performance as the residual of an OLS regression of bonus pay on firm size, industry and occupation dummies, the worker's blue-collar/white-collar status, hierarchical level, and year dummies. The bonus variable we use is observed in year $t+1$ but refers to bonuses earned during year t; thus, we use year-t independent variables in the regression. Panel C of Table 4.1 displays the autocorrelation matrix for the performance measure. As in DeVaro and Waldman (2012) using actual performance (Panel A), and as in the Finnish data using imputed performance (Panel B), in the German data the imputed performance measure is highly autocorrelated, and the strength of the relationship declines with time.

As we noted in the Finnish analysis, a potential issue that arises when workers change firms is that performance related pay is typically paid in year $t + 1$ based on performance in year t. This could lead us to understate the performance of workers who change firms, because a worker who changes firms in period $t+1$ might not receive performance related pay in that year. This issue does not pose a problem for our analysis given that the estimation results in the following section change very little when workers who switch firms and

[29]Since Christmas bonuses might be thought of more as gifts than as performance-based pay, we also conducted the analysis dropping these payments from the bonus measure. Our results of interest are largely unchanged in that case and are available upon request.

received zero performance-related pay are excluded.

4.5 Empirical Analysis: Germany

The empirical analysis using German data parallels the analysis using Finnish data as closely as possible, and the structure of this section parallels the corresponding structure from the Finnish analysis. Table 4.5 displays descriptive statistics for all variables used in the analysis.

4.5.1 Promotion Probability: Germany

We estimate the same multinomial probit model for promotions described earlier in the Finnish analysis. Again the dependent variable is trivariate, where the baseline outcome, 0, is no promotion, outcome 1 is promotion within the firm, and outcome 2 is promotion across firms. The dependent variable refers to the outcome for worker i in year t, whereas all right-hand-side variables are measured in year $t-1$. The independent variables of interest are the dummies for educational attainment, where the middle category (BA) is the reference group. The control variables include worker performance (as defined in the preceding section), age, age squared, experience (in years), experience (in years) squared, job tenure (in years) at the firm, job tenure (in years) at the firm squared, one-digit industry codes, one-digit occupation codes, occupation group (white collar, blue collar, or civil service), and worker's hierarchical level.

Table 4.5: Descriptive Statistics, Germany

	All Workers		Men Only		Women Only	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
Female	0.322	0.467				
Promotion	0.057	0.232	0.060	0.237	0.052	0.223
Firm Change	0.051	0.219	0.051	0.220	0.050	0.217
Demographics						
HS	0.730	0.444	0.749	0.434	0.692	0.462
BA	0.174	0.379	0.155	0.362	0.213	0.410
GRAD	0.096	0.294	0.096	0.295	0.095	0.293
Age	39.970	10.522	40.547	10.347	38.758	10.782
Tenure	11.122	9.523	11.740	9.811	9.822	8.746
Experience	17.382	10.777	18.662	10.864	14.691	10.076
Occupation						
Net Income	21,618	9,323	23,602	9,760	17,447	6,613
Lower Level	0.274	0.446	0.245	0.430	0.336	0.472
Middle Level	0.496	0.500	0.493	0.500	0.504	0.500
Upper Level	0.229	0.420	0.263	0.440	0.160	0.366
Blue-Collar	0.438	0.496	0.532	0.499	0.242	0.428
White-Collar	0.489	0.500	0.385	0.487	0.707	0.455
Civil Servant	0.073	0.259	0.083	0.275	0.051	0.220
Firm Size						
0-19	0.168	0.374	0.157	0.363	0.193	0.395
20-199	0.288	0.453	0.284	0.451	0.296	0.457
200-1999	0.265	0.441	0.258	0.438	0.280	0.449
2000+	0.279	0.448	0.301	0.459	0.231	0.421
Observations	99,748		67,595		32,153	

Source: German SOEP, 1984-2009.

Table 6 displays average marginal effects. Panel A reveals a within-firm promotion rate of 5 percent, which is slightly less than the corresponding rate of 6.2 percent from the Finnish data. As in the Finnish data, most promotions are within-firm, and the probability of across-firm promotion is less than 1 percent. This pattern is true for both men and women, though as in the Finnish data promotion rates are higher for men than women. Six interesting results emerge from Panel A, which combines men and women.

First, as seen in column 1, the probability of within-firm promotion is increasing in the level of educational attainment, holding worker performance in the pre-promotion period constant. This result is the same as that found

Table 4.6: Multinomial Probit, Promotion Within and Across Firms, Germany

Panel A: All Workers

	All Workers		First Promotion		Subsequent Promotion	
	(1) Within	(2) Across	(3) Within	(4) Across	(5) Within	(6) Across
HS	-0.019***	-0.004***	-0.021***	-0.005***	-0.012***	-0.002
	(-8.91)	(-5.22)	(-8.82)	(-5.24)	(-2.95)	(-1.13)
GRAD	0.015***	0.005***	0.019***	0.004***	0.010*	0.008***
	(5.14)	(4.50)	(5.53)	(2.90)	(1.76)	(3.85)
Performance t-1	0.140***	-0.112***	0.174***	-0.121***	0.064	-0.092***
	(4.90)	(-5.60)	(5.18)	(-4.91)	(1.18)	(-2.74)
Female	-0.030***	-0.005***	-0.033***	-0.005***	-0.018***	-0.005***
	(-17.05)	(-7.16)	(-16.40)	(-6.20)	(-5.14)	(-3.31)
Pr(Y=k)	0.050	0.008	0.051	0.008	0.045	0.007
Observations	99,748	99,748	75,796	75,796	23,952	23,952

Panel B: Men

	All Men		First Promotion		Subsequent Promotion	
	(1) Within	(2) Across	(3) Within	(4) Across	(5) Within	(6) Across
HS	-0.019***	-0.003**	-0.024***	-0.003**	-0.009*	-0.002
	(-6.84)	(-2.44)	(-7.32)	(-2.30)	(-1.66)	(-0.91)
GRAD	0.010***	0.003**	0.014***	0.003	0.007	0.004*
	(2.80)	(2.29)	(3.22)	(1.60)	(0.98)	(1.78)
Performance t-1	0.132***	-0.118***	0.182***	-0.119***	0.008	-0.122***
	(4.09)	(-5.17)	(4.83)	(-4.28)	(0.13)	(-2.99)
Pr(Y=k)	0.052	0.008	0.053	0.008	0.048	0.007
Observations	67,595	67,595	50,507	50,507	17,088	17,088

Panel C: Women

	All Women		First Promotion		Subsequent Promotion	
	(1) Within	(2) Across	(3) Within	(4) Across	(5) Within	(6) Across
HS	-0.020***	-0.006***	-0.020***	-0.007***	-0.019***	0.001
	(-6.33)	(-4.71)	(-5.62)	(-5.02)	(-3.13)	(0.17)
GRAD	0.024***	0.008***	0.026***	0.006***	0.018**	0.014***
	(4.93)	(4.58)	(4.66)	(2.88)	(1.97)	(3.50)
Performance t-1	0.196***	-0.113**	0.167**	-0.153***	0.278**	-0.023
	(2.96)	(-2.57)	(2.07)	(-2.77)	(2.55)	(-0.36)
Pr(Y=k)	0.045	0.007	0.047	0.007	0.039	0.006
Observations	32,153	32,153	25,289	25,289	6,864	6,864

Notes: Cell entries are average marginal effects from a multinomial probit, with t-statistics in parentheses. Base Outcome 0: no promotion; Outcome 1: promotion within firm ("Within"); Outcome 2: promotion across firms ("Across"). Row "Pr(Y=k)" refers to the probability of the column's outcome. All right-hand-side variables are measured in year t-1, and the dependent variable is measured in year t. Base education category is the middle education level, BA. All specifications include age, (age) squared, tenure, (tenure) squared, experience, (experience) squared, one-digit industry and occupation codes, firm size, occupation group (white-collar, blue-collar or civil service), worker's hierarchical level controls, and an intercept term.
Source: German SOEP, 1984-2009.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

in DeVaro and Waldman (2012), which considers only white, male stayers and within-firm promotions in a single firm, and it matches the result from the Finnish analysis.

Second, the incremental effects of the education variables are smaller in column 5 than in column 3, suggesting that the previous result is stronger for first promotions than for subsequent promotions. These results are consistent with first promotions having a stronger signaling role than subsequent promotions, as theory predicts and as found in the Finnish analysis. This result also matches what was found in DeVaro and Waldman (2012). We suspect that our evidence in favor of this second result is understated given that our method of distinguishing between first and subsequent promotions likely produces some misclassifications that would blur the distinction between columns 3 and 5.

Third, as seen in column 2 and as found in the Finnish analysis, the result that promotion probability is increasing in the level of educational attainment (controlling for pre-promotion performance) holds for across-firm promotions just as it did for within-firm promotions.

Fourth, as seen by comparing the incremental effects of education in column 4 to those in column 6, it is unclear whether the previous result concerning across-firm promotions is stronger for first promotions than for subsequent promotions. On the one hand, moving from column 4 to column 6, the incremental effect of HS shrinks in magnitude and becomes statistically insignificant. But on the other hand, the incremental effect of GRAD increases in magnitude.

Fifth, as seen in columns 1, 3, and 5 concerning within-firm promotions, the marginal effect of pre-promotion performance has the anticipated positive sign, though it is statistically insignificant in column 5. However, as seen in columns 2, 4, and 6, the sign flips to negative in the case of across-firm promotions. The same pattern of results occurred in the Finnish analysis. As noted there, although one possible explanation for the negative sign for across-firm promotions is adverse selection in the labor market as discussed in Greenwald (1986), we see that explanation as unlikely given that, as will be shown in Table 7, job transitions that occur across firms (whether promotions or not) are associated with wage increases. As noted earlier, we think that a more likely explanation for the negative sign derives from the definition of our performance measure, which is constructed from individual bonus data.

Sixth, the probability of promotion (within and across firms) is lower for women than men. The gender difference in within-firm promotion probabilities (controlling for pre-promotion performance) is three percentage points, which is similar in magnitude to the results from the Finnish analysis and from Blau and DeVaro (2007), both of which control for worker performance.

As in the Finnish analysis, the gender gap is larger for within-firm first promotions than for within-firm subsequent promotions. This result is consistent with first promotions releasing considerable information about the ability of "Invisible" women (using terminology from Milgrom and Oster 1987), thereby diminishing the gender gap in information about abilities.

Panels B and C of Table 6 repeat the preceding analyses for the subsamples of men and women, respectively. The first five results just stated apply both to men and women, though there are two noteworthy differences between these two subsamples. First, the effect of education on promotion differs somewhat between men and women, with education having a larger impact on promotion receipt for women than for men. For the overall sample within firms (column 1), for women a GRAD degree increases the probability of promotion by 2.4% over the baseline education level (BA), whereas for men it increases the probability by only 1.0%. A HS degree reduces the probability of promotion for both men and women almost equivalently (1.9% and 2.0% for men and women, respectively); however, since the within-firm promotion rate for women is 0.7% lower overall than for men, these differences in coefficients understate the effects. This result is consistent with the Milgrom and Oster (1987) argument concerning Visible and Invisibles, in which the education signal is more valuable for women than men. Second, for men, performance is positively related to within-firm promotion receipt in the first-promotion sample, but not in the subsequent-promotion sample, whereas for women performance is even more relevant for subsequent promotions than for first promotions.

4.5.2 Wage Growth and Promotion: Germany

Results for OLS regressions of the wage growth attached to promotions appear in Table 7, which has the same structure as Table 4.4 from the Finnish analysis. First consider Panel A. In contrast to promotion signaling theory, the results in column 1 suggest that the level of educational attainment does not influence the magnitude of the annual wage increase attached to promotions. However, graduate degree holders who switch firms (but without receiving a promotion) experience bigger wage increases than do workers with less education who make the same job transition. Unsurprisingly, last year's performance is positively related to annual wage increases. Annual wage changes are lower for women than men. For our purposes, the most important point to take away from the education-related results in column 1 is that (given that the education variables do not influence the wage changes attached to promotion) there is no empirical support for promotion signaling. This state of affairs does not change when we separate first promotions (column 2) from subsequent promotions (column 3). The promotion-as-signal hypothesis implies that the wage increase from promotion should be decreasing in the level of educational attainment to a greater extent in column 2 than in column 3, whereas in fact there is no evidence of such a pattern in any of columns 1, 2, or 3. Finally, column 1 also reveals some other points. As has been well documented in the literature, within-firm promotions are associated with wage increases. If the promotion involves a change in firms, this wage increase is even larger. Job transitions that occur across firms but do not involve promotion are also associated with big wage increases, relative to remaining in the original firm without a promotion.

If the dependent variable is the change in log-wages (columns 4, 5, and 6) the preceding observations from Panel A continue to hold for within-firm promotions, i.e. there is no evidence of a signaling role of promotions. However, for across-firm promotions there is evidence of signaling except in the case of high school graduates. For that educational group, the interaction with across-firm promotions should be positive according to the theory, whereas it is negative in columns 4, 5, and 6 (though statistically significant only in column 4). The results in DeVaro and Waldman (2012) also fail to support the wage-related predictions of the promotion-as-signal hypothesis for workers with high school degrees. As seen in column 4 and consistent with theory, workers with graduate degrees experience smaller raises upon promotion than do workers with the same job performance but only a college degree. Furthermore, again consistent with theory, this effect is present for first promotions and disappears for subsequent promotions. In summary, Panel A of Table 4 exhibits evidence of promotion signaling for changes in log-wages (with the exception of high school graduates) but not for changes in wage levels.

Comparing the results for men (Panel B) and women (Panel C) reveals some

Table 4.7: OLS Estimates, Changes in Wage Levels and Log-Wage, Germany

Panel A: All Workers

	Wage Levels			Log-Wages		
	(1) All Workers	(2) First Promotion	(3) Subsequent Promotion	(4) All Workers	(5) First Promotion	(6) Subsequent Promotion
HS	-111.823**	-122.117**	-56.636	-0.006**	-0.006**	-0.002
	(-2.04)	(-1.98)	(-0.48)	(-2.48)	(-2.36)	(-0.40)
GRAD	54.411	74.292	-108.263	0.003	0.002	0.001
	(0.52)	(0.61)	(-0.52)	(0.86)	(0.58)	(0.14)
Promotion-Within	356.575*	414.499*	145.385	0.019**	0.024**	-0.003
	(1.72)	(1.76)	(0.35)	(1.99)	(2.17)	(-0.19)
X HS	-9.493	-24.430	80.290	-0.000	-0.004	0.017
	(-0.04)	(-0.10)	(0.18)	(-0.04)	(-0.34)	(1.02)
X GRAD	173.770	7.257	1,018.507	0.009	0.003	0.039
	(0.43)	(0.02)	(1.23)	(0.53)	(0.14)	(1.47)
Promotion-Across	1,631.125***	1,709.914***	1,320.766	0.105***	0.100***	0.127**
	(3.50)	(4.02)	(0.79)	(4.79)	(4.45)	(2.00)
X HS	-698.260	-734.895	-540.639	-0.047*	-0.037	-0.089
	(-1.28)	(-1.38)	(-0.30)	(-1.77)	(-1.30)	(-1.30)
X GRAD	-327.320	-1,294.186	2,385.697	-0.088**	-0.120**	-0.010
	(-0.34)	(-1.18)	(1.13)	(-2.22)	(-2.49)	(-0.14)
No Promotion-Across	667.940**	877.126***	96.593	0.028**	0.040***	-0.003
	(2.53)	(3.00)	(0.17)	(2.39)	(2.81)	(-0.12)
X HS	-18.922	-60.740	20.125	0.014	0.014	0.008
	(-0.07)	(-0.19)	(0.03)	(1.06)	(0.90)	(0.34)
X GRAD	1,190.279**	1,179.855**	1,044.982	0.049**	0.050**	0.034
	(2.44)	(2.34)	(0.83)	(2.31)	(2.14)	(0.75)
Performance t-1	3,494.490***	2,649.726**	5,983.949***	0.092***	0.058	0.192***
	(3.12)	(2.01)	(2.83)	(2.85)	(1.57)	(2.98)
Female	-93.420**	-96.641**	-82.228	0.002	0.002	0.001
	(-2.34)	(-2.18)	(-0.87)	(0.83)	(0.88)	(0.25)
Observations	99,748	75,796	23,952	99,748	75,796	23,952
R^2	0.014	0.016	0.015	0.017	0.020	0.014

Panel B: Men

	Wage Levels			Log-Wages		
	(1) All Men	(2) First Promotion	(3) Subsequent Promotion	(4) All Men	(5) First Promotion	(6) Subsequent Promotion
HS	-130.829	-130.743	-103.391	-0.006*	-0.006*	-0.003
	(-1.64)	(-1.46)	(-0.61)	(-1.91)	(-1.66)	(-0.56)
GRAD	61.874	128.431	-271.252	0.005	0.007	-0.005
	(0.46)	(0.82)	(-1.04)	(1.15)	(1.26)	(-0.63)
Promotion-Within	161.032	248.553	-68.499	0.004	0.010	-0.015

	(0.56)	(0.76)	(-0.12)	(0.38)	(0.82)	(-0.79)
X HS	211.609	167.001	297.909	0.013	0.009	0.028
	(0.69)	(0.48)	(0.48)	(1.16)	(0.68)	(1.24)
X GRAD	690.430	537.784	1,386.588	0.039**	0.036	0.054
	(1.27)	(0.88)	(1.19)	(2.03)	(1.62)	(1.51)
Promotion-Across	1,634.093**	1,816.310***	1,041.300	0.100***	0.091***	0.131
	(2.32)	(2.89)	(0.47)	(3.61)	(3.49)	(1.64)
X HS	-510.106	-690.711	77.464	-0.039	-0.028	-0.075
	(-0.65)	(-0.94)	(0.03)	(-1.19)	(-0.84)	(-0.88)
X GRAD	365.783	-657.838	4,186.491	-0.078	-0.091	-0.020
	(0.24)	(-0.41)	(1.32)	(-1.37)	(-1.38)	(-0.22)
No Promotion-Across	747.292**	874.235**	419.341	0.029**	0.036*	0.011
	(2.00)	(1.98)	(0.59)	(1.97)	(1.93)	(0.50)
X HS	-94.079	-6.096	-426.407	0.011	0.017	-0.014
	(-0.23)	(-0.01)	(-0.54)	(0.68)	(0.83)	(-0.51)
X GRAD	1,478.215**	1,648.970**	716.771	0.051*	0.062**	0.000
	(2.17)	(2.35)	(0.40)	(1.90)	(2.07)	(0.00)
Performance t-1	3,334.793***	2,065.990	6,947.137***	0.087**	0.044	0.213***
	(2.64)	(1.39)	(2.92)	(2.42)	(1.04)	(3.00)
Observations	67,595	50,507	17,088	67,595	50,507	17,088
R^2	0.015	0.018	0.017	0.018	0.021	0.016

Panel C: Women

	Wage Levels			Log-Wages		
	(1) All Women	(2) First Promotion	(3) Subsequent Promotion	(4) All Women	(5) First Promotion	(6) Subsequent Promotion
HS	-99.850	-141.044*	16.265	-0.007*	-0.009**	0.002
	(-1.58)	(-1.95)	(0.12)	(-1.84)	(-2.09)	(0.24)
GRAD	61.800	-29.359	222.757	-0.002	-0.009	0.009
	(0.44)	(-0.20)	(0.65)	(-0.36)	(-1.24)	(0.53)
Promotion-Within	757.386***	743.799***	801.378	0.049***	0.052**	0.032*
	(3.00)	(2.62)	(1.58)	(2.62)	(2.36)	(1.72)
X HS	-465.965*	-414.165	-559.380	-0.028	-0.029	-0.009
	(-1.67)	(-1.33)	(-0.94)	(-1.35)	(-1.23)	(-0.36)
X GRAD	-848.145*	-1,018.776*	139.508	-0.052*	-0.060*	0.001
	(-1.67)	(-1.72)	(0.17)	(-1.92)	(-1.89)	(0.03)
Promotion-Across	1,606.741***	1,534.203***	1,987.719	0.110***	0.109***	0.101
	(3.23)	(2.95)	(1.49)	(3.08)	(2.84)	(1.28)
X HS	-1,093.126	-872.084	-2,839.386*	-0.060	-0.047	-0.160*
	(-1.48)	(-1.10)	(-1.93)	(-1.28)	(-0.91)	(-1.89)
X GRAD	-1,360.703	-2,527.693***	376.596	-0.095*	-0.159***	0.025
	(-1.63)	(-2.71)	(0.25)	(-1.90)	(-2.85)	(0.28)
No Promotion-Across	538.081	826.258**	-657.084	0.027	0.042**	-0.033
	(1.63)	(2.57)	(-0.71)	(1.41)	(2.08)	(-0.71)
X HS	78.801	-159.518	1,051.676	0.019	0.010	0.056

	(0.22)	(-0.44)	(1.06)	(0.88)	(0.45)	(1.11)
X GRAD	545.951	266.325	1,829.439	0.046	0.035	0.106
	(1.01)	(0.45)	(1.41)	(1.40)	(0.95)	(1.44)
Performance t-1	4,216.925*	4,804.066*	2,013.188	0.117	0.117	0.145
	(1.72)	(1.67)	(0.46)	(1.58)	(1.41)	(0.90)
Observations	32,153	25,289	6,864	32,153	25,289	6,864
R^2	0.022	0.026	0.031	0.022	0.025	0.029

Notes: Dependent variables are change in: 1) net yearly wage levels (columns 1-3); and 2) net yearly log-wages (columns 4-6), 2009 Euros. All right-hand-side variables are measured in year t-1, and the dependent variable is measured in year t. Base education category is the middle education level, BA. All specifications include age, (age) squared, tenure, (tenure) squared, experience, (experience) squared, two-digit industry and occupation codes, firm size, occupation group (white-collar, blue-collar or civil service), worker's hierarchical level controls, and an intercept term. t-statistics are shown in parentheses. Source: German SOEP, 1984-2009.
* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

further results. For men, the wage increase (in levels) attached to within-firm first promotions is positive but statistically insignificant, whereas the corresponding result for women is considerably larger in magnitude and statistically significant at the one percent level. For within-firm subsequent promotions, on the other hand, neither gender experiences a statistically significant wage increase. The preceding results also hold in logs, with the only difference being that women continue to experience a positive raise even in the case of within-firm subsequent promotions, though it is still smaller than the raise women receive from within-firm first promotions. This pattern of results is consistent with the Milgrom-Oster framework that predicts larger wage increases from promotion for women than men, with this gender difference dissipating after first promotion.[30]

Further evidence suggesting support for the Milgrom-Oster framework can be found by comparing the education coefficients in Panel B to those in Panel

[30]In the case of across-firm promotions both men and women experience positive and statistically significant wage changes from first promotion but no statistically significant wage change from subsequent promotion.

C. In the case of men, the education-related results do not support the promotion signaling model for either dependent variable. In contrast, in the case of women, whether the dependent variable is changes in wage levels or changes in log-wages, and whether promotions are within firms or across firms, the education-related results are clearly consistent with promotion signaling except for high school graduates. In particular, the interactions of either promotion dummy with the dummy for receipt of a graduate degree exhibit the same pattern of results, namely a negative and statistically significant coefficient in the case of first promotions and a positive and insignificant coefficient in the case of subsequent promotions. The fact that the evidence of asymmetric learning is stronger for women than men is consistent with the argument in Milgrom and Oster (1987) that the abilities of women are less visible to the outside labor market than are the abilities of men. This can be true for a variety of reasons, one of which may be that women benefit less from networking in an "old boys club". Our evidence suggests that this informational disadvantage faced by women is mitigated following the public release of information about abilities that accompanies a first promotion. The basis for this conclusion is that the gender gap (in both promotion probabilities and the wage change conditional on promotion) is present for first promotions but not for subsequent promotions. The evidence suggests that there is significant information content in a first promotion. Prior to that, women may be at a disadvantage relative to men in that their skills are less easily observed by other employers in the labor market. But the positive public signal released when a woman is first promoted tends to level the informational playing field, and thereafter asymmetric learning may be less relevant.

4.6 Summary and Conclusion

We include controls for worker performance in our analyses of promotion probabilities and of the wage growth conditional on promotion, which are crucial in empirical models designed to test the signaling role of promotions. Since such worker performance measures are typically absent in the large-scale panel data sets that span many firms, previous evidence on the signaling role of promotion has had to rely either on single-firm data, as in DeVaro and Waldman (2012) and DeVaro, Ghosh, and Zoghi (2012), or on multi-firm panel data that do not control for worker performance, as in Bognanno and Melero (2012). We overcome this difficulty by constructing a measure of worker performance from individual bonus data, and find that (for both Finland and Germany) its autocorrelation structure is quite similar to that of the actual performance ratings from the single-firm personnel data set used first in Baker, Gibbs, and Holmström (1994a,b) and later in DeVaro and Waldman (2012).[31]

[31]The correlation matrix from DeVaro and Waldman (2012) was matched somewhat more closely by the Finnish matrix than by the German matrix, though here it should be recalled that the German data include white-collar, blue-collar, and civil service workers, whereas the Finnish data include only white-collar workers as in DeVaro and Waldman (2012). Restricting the German analysis to white-collar workers results in a correlation matrix more closely matching that from DeVaro and Waldman (2012).

To summarize the Finnish analysis, the results from both the promotion probability analysis and the wage growth analysis (for both men and women) are consistent with a signaling role of promotion and corroborate the findings in DeVaro and Waldman (2012). That is, for the most relevant case of within-firm promotions, and controlling for pre-promotion worker performance, promotion probability is increasing in the level of educational attainment, and the wage increase conditional on promotion is decreasing in the level of educational attainment for the lowest-level educational group. These results are stronger for first than for subsequent promotions. The fact that the predictions concerning wage growth are unsupported for the highest-level education group echoes the results from DeVaro and Waldman (2012). Furthermore, controlling for pre-promotion worker performance, women experience lower promotion probabilities than men and higher wage growth attached to within-firm promotion than men, but only in the case of first promotions. These results are consistent with the promotion signaling framework in Milgrom and Oster (1987), though only the gender differences in promotion probability are statistically significant and not the gender differences in the wage increases attached to within-firm promotion. Finally, evidence of promotion signaling is weaker in the rarer case of across-firm promotions.

To summarize the German analysis, the probability of promotion is increasing in the level of educational attainment, holding performance in the pre-promotion job constant. This result holds for both within-firm and across-firm promotions, for both men and women, and it is stronger for first promotions than for subsequent promotions. These results are consistent with the signaling role of promotion and the evidence in DeVaro and Waldman (2012). For women (with the exception of high school graduates) the theoretical predictions related to wage changes are also supported. Controlling for performance in the pre-promotion job, the wage change accompanying promotions is decreasing in the level of educational attainment, both for within-firm and across-firm promotions, and whether the wage change is measured in levels or logs. Furthermore, consistent with the theory, these results are present for first promotions but not subsequent promotions. The fact that the predictions concerning wage growth are unsupported for high school graduates echoes the results from DeVaro and Waldman (2012). For men, however, the theoretical predictions concerning wage changes are unsupported. The fact that evidence of asymmetric learning is stronger for women than men is consistent with the arguments in Milgrom and Oster (1987) in which the abilities of women are less visible to employers than are the abilities of men, though our results suggest that this informational disadvantage of women diminishes or vanishes following the first promotion. Further support for the Milgrom-Oster framework is found in the result that, for within-firm first promotions, the wage increase for men is positive but statistically insignificant whereas the corresponding increase for women is considerably larger and statistically significant at the one percent level. Furthermore, for both genders there is no statistically significant wage change associated with within-firm subsequent promotions.

Overall, we see the results from both countries as broadly consistent with a signaling role of promotions, and given the considerable breadth of the Finnish and German samples we see the results as important in establishing the applicability of the promotion-as-signal hypothesis across a wide range of employer types, particularly given that our evidence comes from two distinct economies.

We conclude the analysis with some remarks on the current state of the employer learning literature and how it might fruitfully evolve in the future.[32] Although our focus in this chapter is on asymmetric learning about worker ability in the labor market, a second important perspective in the literature concerns symmetric learning. Under symmetric learning, all employers in the market learn about a worker's abilities at the same rate, so that promotions convey no new information to competing firms.[33] Our impression is that most employment relationships are characterized by at least some asymmetric learning, which would be an argument for preferring that modeling approach. On the other hand, the asymmetric learning model tends to be less analytically tractable than the symmetric learning model, and therefore more difficult to extend and enrich in various dimensions the researcher may wish to explore. Thus, although the asymmetric learning model may offer a more realistic description of the nature of the employer learning that occurs in the labor market,

[32] We are grateful to Mike Waldman for numerous discussions that shaped our thinking on this subject.

[33] Examples of theoretical promotions models based on this assumption are Gibbons and Waldman (1999, 2006), Ghosh (2007), and DeVaro and Morita (2013).

as long as the symmetric learning model offers a reasonable approximation it might be preferable on grounds of tractability. Which of the two perspectives is more appropriate ultimately depends on the production context. These considerations highlight the need for empirical work aimed at discerning the importance of asymmetric learning in promotions, and our work is a step in that direction.

The current empirical evidence suggests that asymmetric learning plays a role, but this same evidence does not rule out the possibility of symmetric learning, nor does it suggest anything about the relative importance of the two types of learning. Empirical studies have generally tended to focus either on tests of symmetric learning (e.g. Farber and Gibbons 1996, Altonji and Pierret 2001, and Lange 2007) or of asymmetric learning (e.g. Schönberg 2007, Kahn 2009, Pinkston 2009, DeVaro and Waldman 2012, and DeVaro, Ghosh, and Zoghi 2012). Collectively, the empirical work in this literature suggests that asymmetric learning plays a role and that symmetric learning also plays a role. What it does not yet do is provide a clear sense of the relative importance of both types of learning, either overall or in a given production context. A promising next step for the literature, therefore, might be developing theoretical frameworks and corresponding empirical frameworks that nest both types of learning so that their relative importance is reflected in estimable parameters. Ideally these frameworks would be developed for application on large-scale, worker-firm matched data sets such as the Finnish data we analyze in this chapter. However, such an approach would require attention to what variables are typically included (and excluded) from such data sets. For example, such data sets typically lack anything resembling an AFQT score, which is a crucial input to the current NLSY-based framework for studying symmetric learning, as developed by Farber and Gibbons (1996), Altonji and Pierret (2001), and Lange (2007). We think that development of a structural empirical framework that nests both types of learning and that does not necessitate data on AFQT scores (so that analysis could move beyond the NLSY to data sets like the Finnish data) would be a significant step forward in this literature. The relative importance of the two types of learning could then be assessed both within and across different job types.

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Chapter 5

Conclusion

My dissertation consists of studies on worker promotions, hierarchical levels, and wage growth.

In my first chapter, I assess the importance of job characteristics on the likelihood that a worker receives a promotion. I assign a four-dimensional skill requirement vector to each occupation as a measure of that occupation's characteristics. These measures are derived from the Dictionary of Occupational Titles. I take labor market histories from the National Longitudinal Survey of Youth 1979, and I fit probit estimations to investigate the determinants of promotion. I find that the skill requirements of an occupation have a significant effect on the probability that the worker receives a promotion. Specifically, I find that higher levels of cognitive skill requirement, and lower levels of motor and strength skill requirements, are associated with higher probabilities of promotion. I also show wage change upon promotion is not greatly impacted by skill requirements, which would otherwise mitigate the impact that a higher promotion probability would have on a worker's career outcome. In addition to impacting promotion receipt directly, I find that including skill requirements changes the effects of other important worker characteristics: the gender gap in promotion is significantly understated when skill requirements are omitted, and including skill requirements increases the gap by 56%, while the importance of Armed Forces Qualification Test scores is greatly reduced when skill requirements are included.

In my second chapter, I estimate an occupational choice model where each occupation is composed of multiple hierarchical levels. Each occupation-level contains a different vector of task usages that describe what activities are performed on that job. Workers search for jobs both across-occupations as well as within-occupations, and accumulate both task-specific and occupation-specific human capital through learning by doing. I take labor market histories from the German Socio-Economic Panel, and I derive task usage information by occupation-level from the German Qualification and Career survey. Using these data, I show three key empirical observations: first, wage losses during unemployment are higher for workers that return to a lower hierarchical level than before unemployment; second, workers in the lowest level have a greater probability of changing occupations than workers in the higher levels; and third, task usage varies significantly within occupations by hierarchical level, with cognitive task usage typically rising, and manual task usage typically falling, as a worker moves to higher levels. I estimate my model using indirect inference. Using the model to simulate worker histories, I show that my model is also able to match well the wage profile and the occupation employment fractions over the worker's life cycle. Also, I find that my model is able to replicate the first two key empirical observations. The specificity of human capital varies by occupation, with blue-collar workers accumulating more occupation-specific skills while white-collar workers accumulate more task-specific skills. Also, the specificity of human capital differs significantly between the model that includes hierarchical levels versus the model that omits levels.

The third and final chapter is coauthored with Jed DeVaro and Antti Kauhanen. In this chapter, we investigate the theory that promotion serves as a signal of worker ability using two large-scale, nationally-representative, European panel data sets, the German Socio-Economic Panel and the Confederation of Finnish Industries. One of the difficulties in using these type of data is that data on worker performance is typically unavailable. We address this problem by fitting regressions of performance-related-pay and bonus data on worker, firm, and job characteristics. Whatever we are not able to explain by observable characteristics, i.e. the residual of these regressions, we assume is the unobserved worker performance and we use these values as our performance measures. We test the first empirical prediction, that education is positively related to promotion receipt, by using probit estimations which include our performance measure. The second empirical prediction, that conditional on promotion, more educated workers receive lower wage gains, is tested using a wage change regression, again controlling for performance using our inferred measure. We find that promotion probabilities are increasing in educational attainment whereas wage increases from promotion are decreasing in educational attainment for some educational groups. Both of these results are stronger for first promotions than for subsequent promotions. We also find that women have lower promotion probabilities than men, though this difference dissipates after the first promotion. Since we are able to follow workers after they leave their current firm, and our hierarchical level assignment procedure not firm-specific, we can separately investigate within-firm versus across-firm promotion. We find that evidence of promotion signaling is stronger for within-firm than for across-firm promotions.

Appendix A

Chapter 2 Appendix

A.1 Additional Tables

Table A-1: Skill Levels: White-Collar

	All Mean/s.d.	Technicians Mean/s.d.	Managers and Prof. Mean/s.d.	Sales Mean/s.d.	Admin. and Support Mean/s.d.
Cognitive	10.23	11.58	10.91	9.16	8.48
	1.66	1.21	0.59	0.98	1.04
Interpersonal	2.82	3.26	3.34	2.87	1.88
	1.26	1.53	0.71	0.25	0.88
Motor	6.24	6.95	5.19	5.09	6.72
	1.69	2.01	0.84	0.44	1.47
Strength	0.17	0.18	0.17	0.23	0.16
	0.13	0.14	0.10	0.06	0.16
Observations	21,551	6,955	6,207	1,538	6,851

Table A-2: Skill Levels: Blue-Collar

	All Mean/s.d.	Service Mean/s.d.	Precision Craft Mean/s.d.	Operators and Laborers Mean/s.d.
Cognitive	6.81	6.53	8.38	5.57
	1.76	1.55	1.33	0.90
Interpersonal	1.32	1.61	1.63	0.92
	0.86	0.72	1.09	0.40
Motor	7.43	6.50	8.47	6.95
	1.52	1.36	1.54	0.94
Strength	0.48	0.45	0.47	0.51
	0.14	0.13	0.15	0.13
Observations	17,995	3,670	6,704	7,621

Table A-3: Skill Level Correlations, Men Only

	Cognitive	Interpersonal	Motor	Strength
Cognitive	1.00			
Interpersonal	0.70	1.00		
Motor	-0.03	-0.45	1.00	
Strength	-0.72	-0.67	0.38	1.00

Table A-4: Skill Level Correlations, Women Only

	Cognitive	Interpersonal	Motor	Strength
Cognitive	1.00			
Interpersonal	0.69	1.00		
Motor	-0.08	-0.42	1.00	
Strength	-0.53	-0.24	-0.02	1.00

Table A-5: Skill Level Correlations: 1970 and 2000 Codes

	1970			
	Cognitive	Interpersonal	Motor	Strength
Cognitive	1.00			
Interpersonal	0.70	1.00		
Motor	-0.04	-0.46	1.00	
Strength	-0.64	-0.51	0.24	1.00
	2000			
	Cognitive	Interpersonal	Motor	Strength
Cognitive	1.00			
Interpersonal	0.68	1.00		
Motor	-0.11	-0.43	1.00	
Strength	-0.61	-0.52	0.38	1.00

Note: 1970 codes include years prior to 2002; 2000 codes include 2002 to 2008

Table A-6: Skill Changes: 1970 and 2000 Codes

	1970		2000	
	All Mean/s.d.	Promoted Only Mean/s.d.	All Mean/s.d.	Promoted Only Mean/s.d.
Cognitive Change	0.27	0.67	0.39	0.96
	2.40	2.45	2.62	2.55
Interpersonal Change	0.14	0.34	0.26	0.58
	1.22	1.32	1.81	1.94
Motor Change	−0.10	−0.26	−0.16	−0.42
	1.94	1.96	2.07	2.08
Strength Change	−0.01	−0.02	−0.03	−0.05
	0.18	0.18	0.21	0.20
Observations	7,040	2,009	1,029	467

Note 1: Only occupation changes included

Note 2: 1970 codes include years prior to 2002; 2000 codes include 2002 to 2008

Table A-7: Skill Levels: AFQT Quintiles

	AFQT1 Mean/s.d.	AFQT2 Mean/s.d.	AFQT3 Mean/s.d.	AFQT4 Mean/s.d.	AFQT5 Mean/s.d.
Cognitive	6.98	7.90	8.58	9.19	10.37
	2.05	2.21	2.19	2.14	2.06
Interpersonal	1.50	1.86	2.09	2.34	2.77
	1.04	1.23	1.26	1.34	1.34
Motor	6.91	6.86	6.81	6.79	6.54
	1.51	1.63	1.74	1.78	1.85
Strength	0.44	0.35	0.31	0.28	0.22
	0.18	0.20	0.20	0.20	0.18
Observations	6,281	8,709	8,036	8,402	8,118

Table A-8: Skill Levels: High School vs College

	High School Mean/s.d.	College Mean/s.d.
Cognitive	7.62	9.59
	2.15	2.24
Interpersonal	1.64	2.57
	1.08	1.36
Motor	7.05	6.54
	1.62	1.76
Strength	0.39	0.25
	0.20	0.19
Observations	18,402	21,144

Table A-9: Promotion Determinants: Marginal Effects of Random Effects Probit, Job Variables, Annual Period (1988-1990)

	All		Men		Women	
	No Skills	Skills	No Skills	Skills	No Skills	Skills
Job						
log Wage	−0.015	−0.034**	−0.023	−0.041**	−0.004	−0.029
	(0.012)	(0.012)	(0.015)	(0.015)	(0.019)	(0.019)
Overtime hours	0.005**	0.005**	0.003	0.004	0.007**	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Union	−0.030**	−0.016	−0.026	−0.012	−0.034*	−0.020
	(0.010)	(0.011)	(0.014)	(0.014)	(0.017)	(0.017)
Medium (100-500)	0.028**	0.027**	0.039**	0.037**	0.015	0.019
	(0.010)	(0.010)	(0.013)	(0.013)	(0.015)	(0.015)
Large(>500)	0.057**	0.055**	0.048**	0.043**	0.064**	0.070**
	(0.011)	(0.011)	(0.015)	(0.015)	(0.016)	(0.016)
Observations	13,992	13,992	8,183	8,183	5,809	5,809

Standard errors in parentheses

Note 1: Dependent variable: promotion receipt between interviews; Time period: 1988-1990; Interviews annual

Note 2: Average marginal effects reported; derivatives w.r.t. entire varlist and continuous approximations of discrete variables

Note 3: Human capital and demographic variables and year dummies included in estimation but not displayed

Note 4: Columns labelled skills include skill requirement levels in estimation

* $p < 0.05$, ** $p < 0.01$

Table A-10: Promotion Determinants: Marginal Effects of Random Effects Probit, Job Variables, Biannual Period (1996-2008)

	All		Men		Women	
	No Skills	Skills	No Skills	Skills	No Skills	Skills
Job						
log Wage	0.007	−0.008	0.009	−0.004	0.003	−0.016
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.010)
Overtime hours	0.001**	0.002**	0.002**	0.002**	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Union	−0.020**	−0.006	−0.007	0.006	−0.042**	−0.030**
	(0.006)	(0.006)	(0.008)	(0.008)	(0.011)	(0.011)
Medium (100-500)	0.019**	0.019**	0.024**	0.023**	0.012	0.014
	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)	(0.008)
Large(>500)	0.053**	0.052**	0.052**	0.050**	0.054**	0.057**
	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)	(0.009)
Observations	25,554	25,554	14,537	14,537	11,017	11,017

Standard errors in parentheses

Note 1: Dependent variable: promotion receipt between interviews; Time period: 1996-2008; Interviews biannual

Note 2: 1970 Codes: 1996-2000; 2000 Codes: 2002-2008

Note 3: Average marginal effects reported; derivatives w.r.t. entire varlist and continuous approximations of discrete variables

Note 4: Human capital and demographic variables and year dummies included in estimation but not displayed

Note 5: Columns labelled skills include skill requirement levels in estimation

* $p < 0.05$, ** $p < 0.01$

Table A-11: Wage Change from Promotion (1988-1990)

	All	Men	Women
Cognitive	-0.001	-0.002	-0.000
	(0.002)	(0.003)	(0.004)
Interpersonal	-0.006	0.003	-0.013^{*}
	(0.004)	(0.006)	(0.006)
Motor	-0.005^{*}	-0.002	-0.009^{**}
	(0.002)	(0.003)	(0.003)
Strength	-0.008	0.018	-0.022
	(0.023)	(0.037)	(0.035)
Observations	5,371	3,146	2,225

Standard errors in parentheses
Note 1: Dependent variable in log wage change.
Note 2: All specifications control for age, tenure, experience, race, year, and industry.
* $p < 0.05$, ** $p < 0.01$

Table A-12: Wage Change from Promotion (1996-2008)

	All	Men	Women
Cognitive	-0.007	-0.005	-0.009
	(0.004)	(0.005)	(0.008)
Interpersonal	-0.007	-0.005	-0.009
	(0.007)	(0.008)	(0.011)
Motor	-0.008	-0.010	-0.006
	(0.004)	(0.006)	(0.008)
Strength	-0.034	0.023	-0.094
	(0.042)	(0.062)	(0.069)
Observations	1,293	711	582

Standard errors in parentheses
Note 1: Dependent variable in log wage change.
Note 2: All specifications control for age, tenure, experience, race, year, and industry.
* $p < 0.05$, ** $p < 0.01$

Appendix B

Chapter 3 Appendix

B.1 Hierarchical Level Assignment

In this appendix I describe the procedure used to assign job levels in both the GSOEP and GQCS. The basis for the assignment is the skill level of the worker's main job. Note that the worker is not asked about his or her own skill level but rather the skill level requirement or task complexity of the job. Fortunately, the wording of the occupational status question has remained essentially unchanged throughout the entire GSOEP panel history, so that consistent hierarchical assignment across time is possible. It is also consistent across both the 1986 and 1992 waves of the GQCS. The occupational status question for the 1985 GSOEP survey for blue-collar, white-collar, and civil servants is as follows:[1]

What position do you have at the moment? If you have more than one job at the moment, please answer the following in reference to your main job.

Blue-collar worker:

unskilled worker **(1)**
trained worker **(2)**
semi-skilled and skilled worker **(3)**
foreman **(4)**

[1] Since self-employed workers and trainees are dropped from our sample, their sections of the question are omitted.

White-collar worker:

industry and works foreman in nontenured employment

employee with simple duties (e.g. salesperson, clerk, stenotypist) **(1)**

employee with qualified duties (e.g. official in charge, technical drawer) **(2)**

employee with highly qualified duties or managerial function (e.g. scientific worker, attorney, head of department) **(3)**

employee with extensive managerial duties (e.g. manager, managing director, head of a large firm or concern) **(4)**

Civil servant (including judges and professional soldiers):

lower level **(1)**

middle level **(2)**

upper level **(3)**

executive level **(4)**

Note that the worker can only answer yes to one of the preceding options, and his or her response to the question determines blue-collar, white-collar or civil service status. The number in parentheses after some of the responses indicates the level to which a worker responding with that answer is assigned. Following Lluis (2005), I do not assign the "industry and works group" in the white-collar category to a level, as it is unclear where these employees should be placed. For Chapter 2 I assign all level 4 workers into level 3.

B.2 Value Functions

Specifying the worker's value function is straightforward but tedious. This is due to the large number of different potential options each period arising from the search process. First, I start by specifying the value function for a worker in unemployment in period t:

$$\begin{aligned} U_t(S_{it}) =& u_{j=0,t}(S_{it}) + \beta E[(1-\phi_1) * U_{t+1}(S_{i,t+1}) + \\ & \phi_1(\phi_2(\sum_{l=1}^{L} \kappa_l^1 max\{U_t(S_{i,t+1}), V_{1l,t+1}(S_{i,t+1})\}) + \\ & (1-\phi_2)(\sum_{l=1}^{L} \kappa_l^2 max\{U_t(S_{i,t+1}), V_{2l,t+1}(S_{i,t+1})\}))] \end{aligned}$$

Note that, even when the worker receives an job offer, they still have the option of remaining in unemployment. Next, the value function of a worker employed in occupation j, level l in period t:

$$
\begin{aligned}
V_{jlt}(S_{it}) =& u_{jlt}(S_{it}) + \beta E[\psi^j((1-\phi_1) * U_{t+1}(S_{i,t+1}) + \\
& \phi_1(\phi_2(\sum_{l=1}^{L} \kappa_l^1 max\{U_{t+1}(S_{i,t+1}), V_{1l,t+1}(S_{i,t+1})\}) + \\
& (1-\phi_2)(\sum_{l=1}^{L} \kappa_l^2 max\{U_{t+1}(S_{i,t+1}), V_{2l,t+1}(S_{i,t+1})\})) + \\
& (1-\psi^j)(\nu_1^j(\sum_{l=1}^{L} \kappa_l^j max\{U_{t+1}(S_{i,t+1}), V_{jl,t+1}(S_{i,t+1})\})) + \\
& (1-\nu_1^j)(\nu_2^j(\sum_{l=1}^{L} \kappa_l^{j-1} max\{U_{t+1}(S_{i,t+1}), V_{j_{-1}l,t+1}(S_{i,t+1})\}) + \\
& (1-\nu_2^j) max\{U_{t+1}(S_{i,t+1}), V_{1l,t+1}(S_{i,t+1})\})))]
\end{aligned}
$$

Where j_{-1} refers to the other occupation. Numerous different events can occur to an employed worker. These include suffering a job loss, suffering a job loss but immediately receiving a new job offer, receiving a within-occupation job offer, and receiving an across-occupation job offer. Finally, S_{it} evolves according to Equations (3.2) and (3.3).

B.3 Model Fit: No Levels

Figure B.1: Overall Wages, No Levels

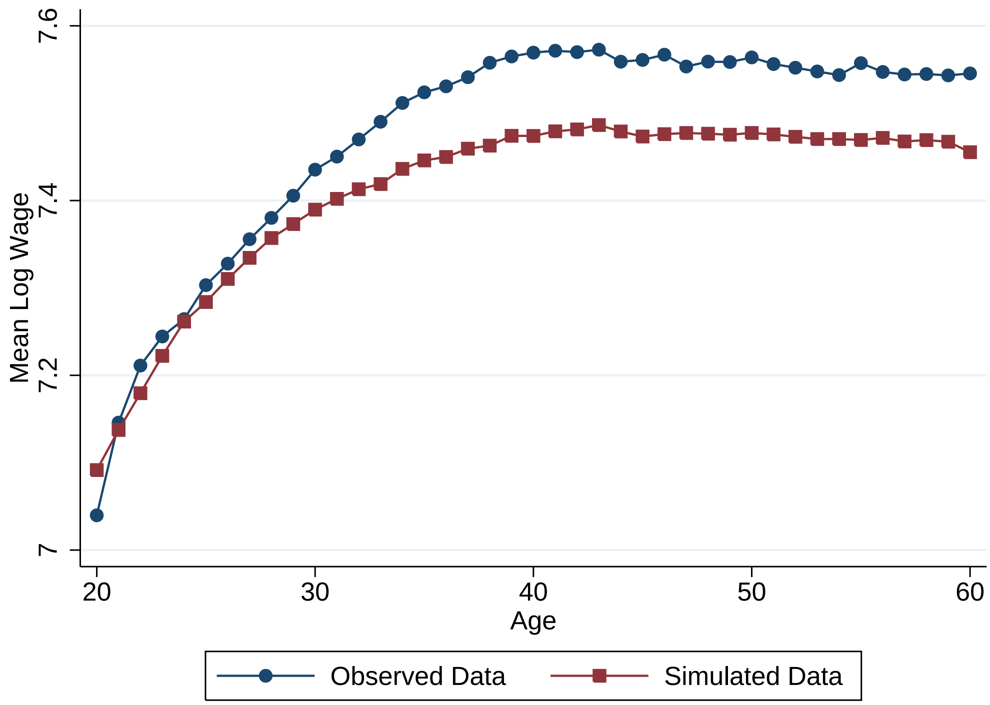


Figure B.2: Wages: Blue-Collar, No Levels

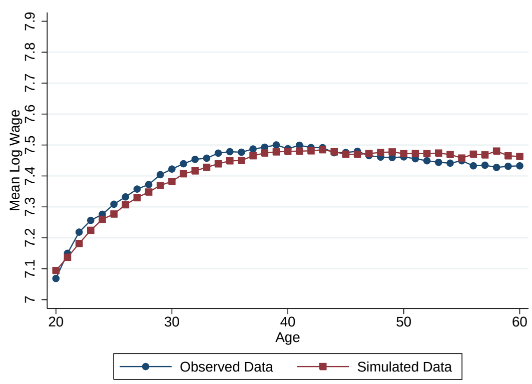


Figure B.3: Wages: Blue-Collar, No Levels

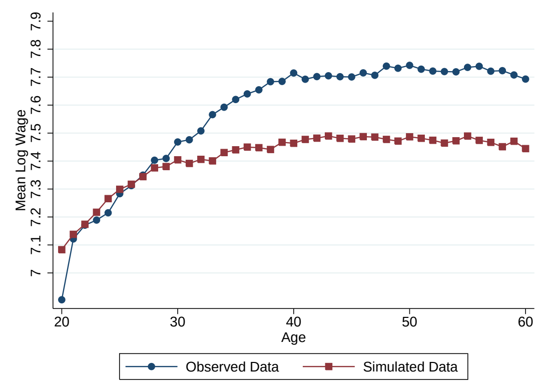


Figure B.4: Occupation Composition, No Levels

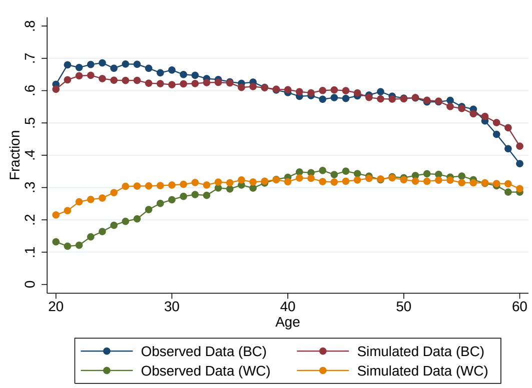
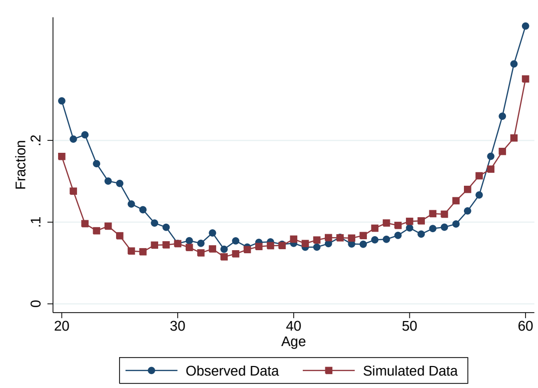


Figure B.5: Unemployment, No Levels



B.4 Auxiliary Model Moments

Table A-1: Auxiliary Model: Fixed Effect Wage Regression

	Data	Model
τ_{it}	0.0792359	0.146504
	(0.0120271)	(0.0114068)
t	0.0134151	-0.00142
	(0.0010218)	(0.0015451)
t^2	-0.0004912	-0.00051
	(0.0000106)	(0.000011)
$exp_{1,it} * \mathbb{1}(j=1)$	0.0256619	0.067642
	(0.0017627)	(0.0017558)
$exp_{2,it} * \mathbb{1}(j=2)$	-0.0024922	0.024357
	(0.0025122)	(0.0025009)
$exp^2_{1,it} * \mathbb{1}(j=1)$	-0.0021433	-0.00239
	(0.0001556)	(0.0001675)
$exp^2_{2,it} * \mathbb{1}(j=2)$	-0.0008734	-0.00108
	(0.000219)	(0.0002288)
$exp^3_{1,it} * \mathbb{1}(j=1)$	0.0000543	2.99E-05
	(0.0000044)	(0.00000498)
$exp^3_{2,it} * \mathbb{1}(j=2)$	0.0000292	0.000029
	(0.00000606)	(0.00000675)
exp_{it}	0.0164093	-0.02579
	(0.0018337)	(0.0021369)
exp^2_{it}	-0.0001338	0.001137
	(0.0000619)	(0.0000603)
$cogsum_{it} * \tau_{it}$	0.0617233	0.128395
	(0.0055294)	(0.0053761)
$cogsum^2_{it} * \tau_{it}$	-0.0012552	-0.0042
	(0.0004111)	(0.0004009)
Constant	7.274401	7.525145
	(0.0155622)	(0.0237668)
	N = 45316	$\bar{N}$ = 45860.25
	R^2(within) = 0.175	R^2(within) = .216
	R^2(between) = 0.016	R^2(between) = .002
	R^2(overall) = 0.048	R^2(overall) = .004

Table A-2: Auxiliary Model: Event Probabilities

Event	Data	Model
Employment to Unemployment:		
Blue-Collar $->$ Unemp	0.0401	0.052
White-Collar $->$ Unemp	0.0181	0.027
Unemployment to Employment:		
Unemp $->$ BC 1	0.482	0.318
Unemp $->$ BC 2	0.313	0.385
Unemp $->$ BC 3	0.259	0.435
Unemp $->$ WC 1	0.076	0.113
Unemp $->$ WC 2	0.074	0.115
Unemp $->$ WC 3	0.029	0.025
Promotion/Demotion:		
Promotion (BC)	0.052	0.037
Promotion (WC)	0.068	0.050
Demotion (BC)	0.066	0.050
Demotion (WC)	0.045	0.019

Table A-3: Auxiliary Model: Employment to Unemployment Regression

	Data	Model
$wage_{i,t-1}$	-0.06309	-0.02707
	(0.0029528)	(-0.0028215)
Constant	0.506511	0.246049
	(0.0221727)	(0.0211382)
	N = 39392	$\bar{N}$ = 41873.5
	R^2 = 0.012	R^2 = 0.002

Table A-4: Auxiliary Model: Linear Probability Regressions

	Blue-Collar					
	Level 1		Level 2		Level 3	
	Data	Model	Data	Model	Data	Model
t	-0.00041	-0.00397	-0.00661	7.03E-06	0.007586	0.001162
	(0.0001826)	(0.0001836)	(0.0008779)	(0.0008692)	(0.0004497)	(0.0004502)
t^2			3.87E-05	6.84E-06	-0.00015	-9.17E-06
			(0.0000183)	(0.0000183)	(0.00000936)	(0.00000948)
	N = 50578	$\bar{N}$ = 50589.5	N = 50578	$\bar{N}$ = 50589.5	N = 50578	$\bar{N}$ = 50589.5
	R^2 = 0.0001	R^2 = 0.009	R^2 = 0.012	R^2 = 0.0002	R^2 = 0.006	R^2 = 0.001
	White-Collar					
	Level 1		Level 2		Level 3	
	Data	Model	Data	Model	Data	Model
t	-0.00103	-0.00222	0.012404	0.006228	0.003102	0.001497
	(0.0004022)	(0.0004252)	(0.0007232)	(0.0007503)	(0.0001159)	(0.0001133)
t^2	1.72E-05	2.53E-05	-0.00023	-0.00013		
	(0.00000837)	(0.00000895)	(0.0000151)	(0.0000158)		
	N = 50578	$\bar{N}$ = 50589.5	N = 50578	$\bar{N}$ = 50589.5	N = 50578	$\bar{N}$ = 50589.5
	R^2 = 0.0002	R^2 = 0.003	R^2 = 0.006	R^2 = 0.002	R^2 = 0.014	R^2 = 0.004

Table A-5: Auxiliary Model: Wage Change Regression

	Data	Model
$\frac{1}{log(t)} * \tau_{i,t-1} * \tau_{it}$	0.053254	0.074325
	(0.0134531)	(0.0141713)
$\frac{1}{log(t)}$	0.20257	0.178783
	(0.012046)	(0.0125158)
$exp_{j,it}$	-0.00081	0.00053
	(0.0001865)	(0.0002243)
Constant	-0.05155	-0.05514
	(0.0048188)	(0.0050784)
	N = 38086	$\bar{N}$ = 40052
	R^2 = 0.010	R^2 = 0.006

Table A-6: Auxiliary Model: Initial Wages

	Blue-Collar					
	Level 1		Level 2		Level 3	
	Data	Model	Data	Model	Data	Model
Mean	7.111	7.168	7.145	7.167	7.433	7.290
S.D.	0.310	0.281	0.298	0.271	0.279	0.322

	White-Collar					
	Level 1		Level 2		Level 3	
	Data	Model	Data	Model	Data	Model
Mean	7.005	7.108	7.145	7.229	7.457	7.388
S.D.	0.307	0.300	0.254	0.344	0.254	0.380

Table A-7: Auxiliary Model: Wages by Age

	Data			Model		
	Age 29-31	Age 39-41	Age 54-56	Age 29-31	Age 39-41	Age 54-56
Blue-Collar Level 1	7.37	7.42	7.38	7.43	7.47	7.43
Blue-Collar Level 2	7.43	7.51	7.47	7.42	7.44	7.43
Blue-Collar Level 3	7.57	7.65	7.61	7.88	7.55	7.55
White-Collar Level 1	7.31	7.4	7.43	7.28	7.3	7.39
White-Collar Level 2	7.47	7.53	7.63	7.52	7.62	7.7
White-Collar Level 3	7.58	7.91	7.99	7.62	7.81	7.89

Table A-8: Auxiliary Model: Wage Change by Events

Event	Data	Model
No Change	0.0131	0.0114
Promotion	0.0358	0.102
Demotion	-0.0052	-0.006
Occupation Change	0.0162	0.0370
Unemployment Spell	-0.0342	-0.121

Table A-9: Auxiliary Model: Overall Occupation-Level Make-up

	Data			Model		
	Age 18-30	Age 31-50	Age 51-60	Age 18-30	Age 31-50	Age 51-60
Blue-Collar Level 1	0.261	0.243	0.243	0.301	0.260	0.191
Blue-Collar Level 2	0.374	0.290	0.234	0.284	0.279	0.283
Blue-Collar Level 3	0.033	0.069	0.050	0.047	0.057	0.069
White-Collar Level 1	0.053	0.042	0.046	0.070	0.049	0.038
White-Collar Level 2	0.123	0.186	0.164	0.165	0.194	0.179
White-Collar Level 3	0.020	0.093	0.114	0.050	0.083	0.093
Unemployment	0.137	0.076	0.147	0.083	0.078	0.146

Table A-10: Auxiliary Model: Occupation Change by Occupation and Age

	Data	Model
Blue-Collar		
Age 18-30	0.029	0.026
Age 31-45	0.028	0.023
Age 46-60	0.023	0.017
White-Collar		
Age 18-30	0.062	0.047
Age 31-45	0.034	0.040
Age 46-60	0.035	0.031

Table A-11: Auxiliary Model: Other Moments

	Data	Model
S.D. Ind. Wages	0.147	0.157
Mean Wage Before Unemp	7.327	7.406
Mean Wage After Unemp	7.236	7.265
Unemployment Make-up by Age:		
Age 18	0.561	0.562
Age 19	0.382	0.308
Age 20	0.248	0.188

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